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Technical Memorandum

ADDITIONAL STUDIES OF FOREST CLASSIFICATION ACCURACY AS INFLUENCED BY MULTISPECTRAL SCANNER SPATIAL RESOLUTION

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16. Abstract

Two investigations were conducted in order to address unresolved issues raised in a recent investigation [1] of multispectral scanner spatial resolution for forest surveys. First, an analysis of forest feature signatures was used to help explain the large variation in classification accuracy that can occur among individual forest features for any one case of spatial resolution and the inconsistent changes in classification accuracy that were demonstrated among features as spatial resolution was degraded. Second, the classification rejection threshold was varied in an effort to reduce the large proportion of unclassified resolution elements that previously appeared in the processing of coarse resolution data when a constant rejection threshold was used for all cases of spatial resolution.

For the signature analysis, two-channel ellipse plots showing the feature signature distributions for several cases of spatial resolution indicated that the capability of signatures to correctly identify their respective features is dependent on the amount of statistical overlap among signatures. Reductions in signature variance that occur in data of degraded spatial resolution may not necessarily decrease the amount of statistical overlap among signatures having large variances and small mean separations. Features classified by such signatures may thus continue to have similar amounts of misclassified elements in coarser resolution data, and thus, not necessarily improve in classification accuracy.

Additional analyses of forest feature signatures suggested three trends for training data and signature properties as spatial resolution was degraded. These were a) that real data values within individual training areas tended to approach a multivariate normal distribution more closely; b) that small differences existed in the rates of decrease among signature determinant values; and c) that correlations decreased between channels of a spectral signature.

Adjustment of the classification rejection threshold to maintain a constant proportion of unclassified resolution elements among all cases of spatial resolution caused significant increase in the overall classification accuracy of (64 meters)^2 data. The recommendation for future operational systems is that rejection thresholds be selected with great care, and not set at an arbitrary constant value.

Ref. 1. Sadowski, F., and J. Sarno, Forest Classification Accuracy as Influenced by Multispectral Scanner Spatial Resolution, Report No. 109600-71-F, Environmental Research Institute of Michigan, Ann Arbor, Michigan, May 1976.

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PREFACE

This report describes part of a comprehensive and continuing program of research concerned with advancing the state-of-the-art in remote sensing of the environment from aircraft and satellites. The research is being carried out for NASA's Lyndon B. Johnson Space Center, Houston, Texas, by the Environmental Research Institute of Michigan (ERIM). The basic objective of this multidisciplinary program is to develop remote sensing as a practical tool to provide the planner and decision-maker with extensive information quickly and economically.

Timely information obtained by remote sensing can be important to such people as the farmer, the city planner, the conservationist, and others concerned with problems such as crop yield and disease, urban land studies and development, water pollution, and forest management. The scope of our program includes:

1. extending the understanding of basic processes
2. discovering new applications, developing advanced remote-sensing systems, and improving automatic data processing to extract information in a useful form
3. assisting in data collection, processing, analysis, and ground-truth verification.

The research described herein was performed under NASA Contract No. NAS9-14988, Task 5. R. E. Joosten (TF5) was the NASA Task Technical Monitor. The program was directed by Richard R. Legault, Vice President of ERIM and Head of the Infrared and Optics Division, Quentin Holmes, Head of the Information Systems and Analysis Department, and Richard F. Nalepka, Principal Investigator and Head of the Multispectral Analysis Section. William A. Malila served as Task Leader.

The authors wish to acknowledge the technical direction and assistance provided by R. F. Nalepka and W. A. Malila. The ERIM number of this technical memorandum is 122700-4-R.

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FIGURES (CONT.)

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ADDITIONAL STUDIES OF FOREST CLASSIFICATION ACCURACY AS INFLUENCED BY MSS SPATIAL RESOLUTION

SUMMARY

This technical memorandum presents the results of investigations conducted in order to address two unresolved issues raised in the report entitled, "Forest Classification Accuracy as Influenced by Multispectral Scanner Spatial Resolution"[1].

These issues were: (1) the large variation in classification accuracy manifested by individual forest features for any one case of spatial resolution and the inconsistent changes in classification accuracy demonstrated among features as spatial resolution was degraded, and (2) the large proportion of unclassified resolution elements that appeared in coarse resolution data as a result of using a constant classification rejection threshold. The respective approaches of these investigations consisted of a signature analysis to help explain classification performance for individual features and a variation of the rejection threshold for classifying coarse resolution data.

For the signature analysis, two-channel ellipse plots for pairs of channels most optimal for discriminating the features were generated to illustrate the more significant statistical differences and similarities among the multivariate signature distributions. Analysis of the plots showed that the capability of signatures to identify their respective features is dependent on the amount of statistical overlap among signatures which causes resolution element misclassification. Reductions in signature variance that occur in data of degraded spatial resolution may not necessarily decrease the amount of statistical overlap among signatures having large variances and small mean separations. Features classified by such signatures may thus continue to have similar amounts of misclassified elements in coarser resolution data, and thus, not necessarily improve in classification accuracy.

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A simulation of feature classification
was performed under the assumption that the data
values within feature training areas had multi-
variate normal distributions at each case of spa-
tial resolution. Comparison of the simulated to
the real classification results suggested that the
real data values within training areas tended to
approach a normal distribution more closely as
spatial resolution was degraded. Additional anal-
ysis showed that small differences in rates of de-
crease among signature determinant values existed
as spatial resolution was degraded. Finally, evi-
dence was provided to suggest that correlations
between channels of a spectral signature decrease
as spatial resolution is degraded.

Adjusting the classification rejection
threshold to maintain a constant proportion of
unclassified resolution elements among all cases
of spatial resolution caused significant increase
in the overall classification accuracy of $(64 \text{ meters})^2$
data. Because unclassified elements are typically
considered to be classification errors, results of
the previous study [1] had shown that $(32 \text{ meters})^2$
resolution provided the most accurate element-by-
element classification of the data, due to a
large proportion of unclassified elements in
$(64 \text{ meters})^2$ data. If the proportion of unclassi-
fied elements is reduced by adjusting the rejection
threshold, then $(64 \text{ meters})^2$ resolution provides the
best overall classification performance. The recom-
mendation for future operational systems is
that rejection thresholds be selected with great
care, and not set at an arbitrary constant value.

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INTRODUCTION

The purpose of this technical memorandum is to provide the
results of investigations into the influence of multispectral scanner
spatial resolution on forest classification accuracy. These investi-
gations were conducted in order to address two unresolved issues raised
in a recent report entitled "Forest Classification Accuracy as Influenced
by Mulitspectral Scanner Spatial Resolution" [1]. Specifically,
these issues were: a) the large variation in classification accuracy
manifested by individual condition class forest features and the incon-
sistent changes in classification ~ccuracy demonstrated among features
as spatial resolution was degraded; and b) the large proportion of
unclassified resolution elements that appeared in coarse resolution data
as a result of using a constant classification rejection threshold.

1.1 RESULTS OF PREVIOUS STUDY

For the study cited, the influence of multispectral scanner (MSS)
spatial resolution on forest classification accuracy was determined for
forest features at several levels of detail or hierarchies that might be
appropriate for detailed in-place inventories and nationwide forest
surveys. The most detailed hierarchy of features constituted condition
classes (forest cover types differentiated into stands on the basis of
age and size class) that were identified on U.S. Forest Service maps.
A supervised classification procedure that utilized signatures extracted
from training areas in each such feature was used to classify MSS data
of inherent (2 meters)^2 spatial resolution collected over two separate
ground areas of the Sam Houston National Forest. Classification perfor-
mance, determined for the hierarchy of condition class features, was
stated for three regions within the data set that included the training
areas within each feature area, entire feature areas with boundary elements
excluded (boundary exclusive test sets), and entire feature areas with

boundary elements included (boundary inclusive test sets). The results were then aggregated to provide a measure of classification performance for more general hierarchies of features. For the five pine features within Data Segment 1, condition classes were combined into cover type features on the basis of species, and alternately, into features based on maturity that were called growth stages. For the most general hierarchy, all pine sawtimber features were combined into single physiognomic feature for Data Segment 1 and two condition classes of hardwood sawtimber were combined into a single physiognomic feature within Data Segment 2.

The data were then progressively coarsened to simulate five additional data sets having $(4)^2$, $(8)^2$, $(16)^2$, $(32)^2$ and $(64 \text{ meters})^2$ spatial resolution. Similar processing and analysis of all spatial resolutions determined that classification accuracy improved for all hierarchies of features as spatial resolution degraded from $(2 \text{ meters})^2$ to $(32 \text{ meters})^2$ when conventional single-element multispectral processing procedures were used. Improvement in classification accuracy as resolution degraded was attributed to a reduction in the number of misclassified resolution elements that occurred as a result of reduced competition among signature distributions. Reduced competition presumably resulted from a reduction in scene variation that is inherent in the averaging of information over larger ground areas. Improvements in classification accuracy noted for hierarchies of more general (aggregated) forest features occurred by virtue of the fact that misclassifications of resolution elements between certain specific features cancelled for their aggregated feature class.

Two somewhat unexpected phenomena were noted as part of the results. One concerned the classification performance for individual forest features. In determining the general significance of spatial resolution, overall classification accuracies for hierarchies were derived from the total correct classification for all features contained within the hierarches and found to improve as resolution degraded. However, results

for individual features within the hierarchy of condition classes showed
that classification accuracies can vary widely from feature to feature
for any one case of spatial resolution. More importantly, the trends
in classification accuracy as a function of spatial resolution were not
entirely uniform from feature to feature. Some features were consist-
ently better classified in coarser resolution data and some were not.

A second unexpected phenomenon resulted from the use of a constant
classification rejection threshold for all cases of spatial resolution.
When spatial resolution was degraded to (64 meters)^2, the percentage
of unclassified elements in test sets increased greatly. Because
unclassified elements were considered to be errors, this caused a net
decrease in classification accuracy.

1.2 ISSUES ADDRESSED IN THIS MEMORANDUM

Reported herein are the results of two investigations whose
respective approaches consisted of a signature analysis to help explain
classification performance for individual features and a variation of the
rejection threshold for classifying coarse resolution data.

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FEATURE SIGNATURE ANALYSIS

2.1 BACKGROUND

Figures 1 and 2 display the classification accuracies that were achieved previously [1] at each case of spatial resolution for individual features in each of the two data segments. These accuracies were achieved for training areas from which the signatures were extracted. Classification accuracies for whole feature areas were shown in Ref. 1 to be lower, due to the larger variation across the entire area of a feature that may not be represented within the training area. By showing classification performance for training areas, we represent an upper limit of performance that assumes each feature area is adequately described by its respective signature(s). Thus, the results are uncomplicated by the additional confusion to the classification performance that may be introduced by nonuniformities within non-training portions of the features, boundary elements, etc.

Both figures illustrate wide variations in feature classification accuracy for any one case of spatial resolution. For example, with $(2 \text{ meters})^2$ data in Data Segment 1, 51.1% of the Pine Regeneration Feature was classified correctly while Mature Loblolly Pine was only 16.9% correct. The discrepancies among feature classification accuracies are even greater for Data Segment 2, with a 52.9% difference in accuracy between the two hardwood condition class features in $(2 \text{ meters})^2$ data.

For Data Segment 1, three of the features display more or less consistently better classification accuracies as spatial resolution degrades, while the remaining two generally stay low, undulating slightly from better to poorer performance and back, out to the $(32 \text{ meters})^2$ case of resolution. The dramatic increases in accuracy
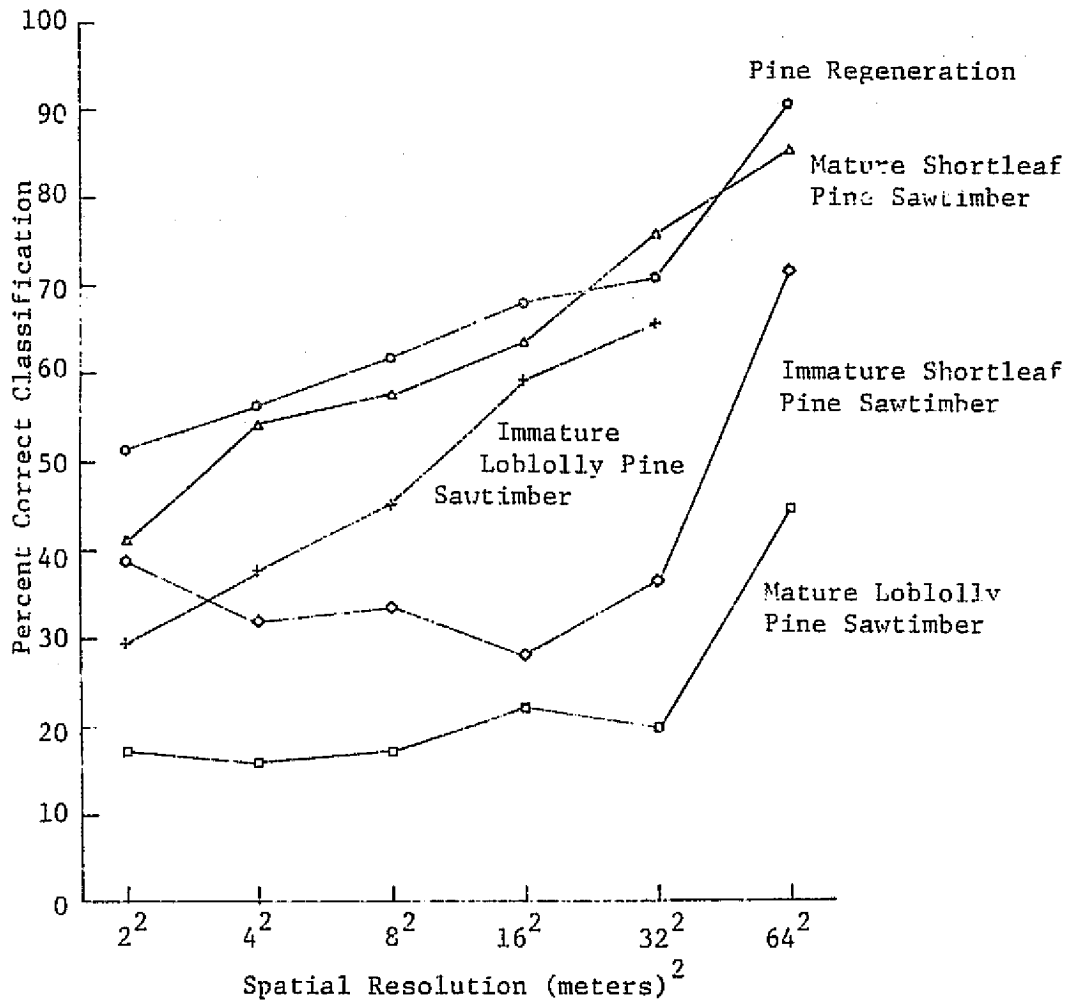
FIGURE 1. CLASSIFICATION ACCURACIES FOR INDIVIDUAL CONDITION CLASS FEA-
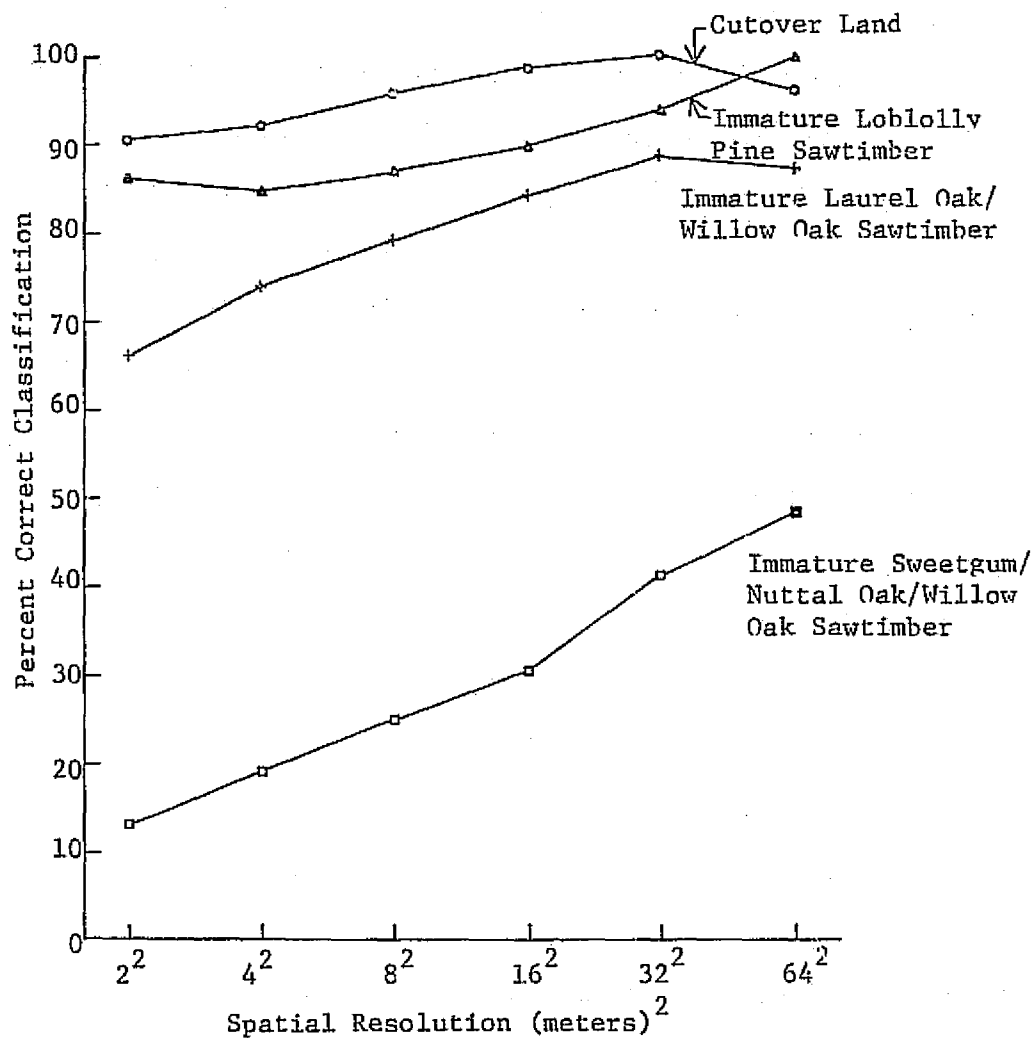TURES WITHIN DATA SEGMENT 1 AT EACH CASE OF SPATIAL RESOLUTION

FIGURE 2. CLASSIFICATION ACCURACIES FOR INDIVIDUAL CONDITION CLASS FEA-
TURES WITHIN DATA SEGMENT 2 AT EACH CASE OF SPATIAL RESOLUTION

for (64 meters)^2 data are probably due to the fact that one less sig-
nature was used to classify training areas because one class contained
insufficient resolution elements to form a valid signature.

For Data Segment 2, classification accuracies for all features
generally improve out to (32 meters)^2. [Immature Loblolly Pine pro-
vides the one exception for (4 meters)^2 resolution.] Decreases in
accuracy for the Cutover Feature and Immature Laurel Oak/Willow Oak
Sawtimber at (64 meters)^2 were caused by a substantial increase in the
number of resolution elements that were unclassified (See Sec. 3).

2.2 PROCEDURE

To analyze feature signatures, we generated two-channel ellipse
plots of the signatures in each data segment for several cases of
spatial resolution. For each case of spatial resolution, the plots
of signature ellipses provided a graphic illustration of the relative
locations, sizes, and orientations of the feature signatures in two-
channel space. By choosing pairs of channels most optimal for the
discrimination of all features, such two-channel plots can illustrate
the more significant statistical differences and similarities among
the multivariate signature distributions. It was found that much of
the classification performance for the forest features could be
explained by noting the relationships among signatures in each plot.

To gain further insight into the effect of degraded spatial
resolution on the feature signatures, we simulated classification per-
formances under the assumption that the data values within feature
training areas at each case of spatial resolution had multivariate
normal distributions, and also examined relative rates of decrease of
signature determinants and dispersion volumes. Departures from nor-
mality on the part of the actual data distributions and non-uniform
rates of change in dispersion volume among the signatures may offer

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additional explanations of the observed trends in classification accuracies for individual features.

To determine the departures from normality for the actual data distributions within the training areas, we compared the ideal performance to be expected for classifying data values known to be distributed in a normal manner to the classification performance achieved for the real data. The ideal expected classification performance for each feature was simulated by computing classification probabilities among the signatures of each data segment. For each signature taken in turn, 2000 data values were generated at random according to the signature's specified multivariate normal distribution and then classified appropriately as one of the feature signatures. The fractions of data values assigned to each feature signature provided an estimate of the probability that data values within one feature area would be correctly classified, misclassified as another feature, or remain unclassified. The classification algorithm, decision boundaries, and classification rejection threshold were the same as those used to classify the real data values in the training areas.

To examine the relative rates of decrease for signature determinants, we plotted the determinant values of all signatures in Data Segment 1 as a function of spatial resolution. A final plot, showing the ratio of dispersion volume to the product of the 11 channel standard deviations for two signatures as a function of spatial resolution, was made to allow observation of the relative amount of between-channel correlations of the signature distributions as resolution was degraded.

2.3 RESULTS

2.3.1 ANALYSIS OF SIGNATURE PLOTS

Figures 3-6 illustrate, for two dimensions, the signature distributions for features of Data Segment 1 at resolutions of $(2)^2$, $(8)^2$, $(32)^2$, and $(64 \text{ meters})^2$, respectively. Figures 7 and 8

FIGURE 3. SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 1 -- (2 METERS)^2 RESOLUTION

FIGURE 4. SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 1 -- (8 METERS)^2 RESOLUTION

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FRP M25 SIGNATURES (SHNF. NOV.74)
DATA SEGMENT 1. 32M
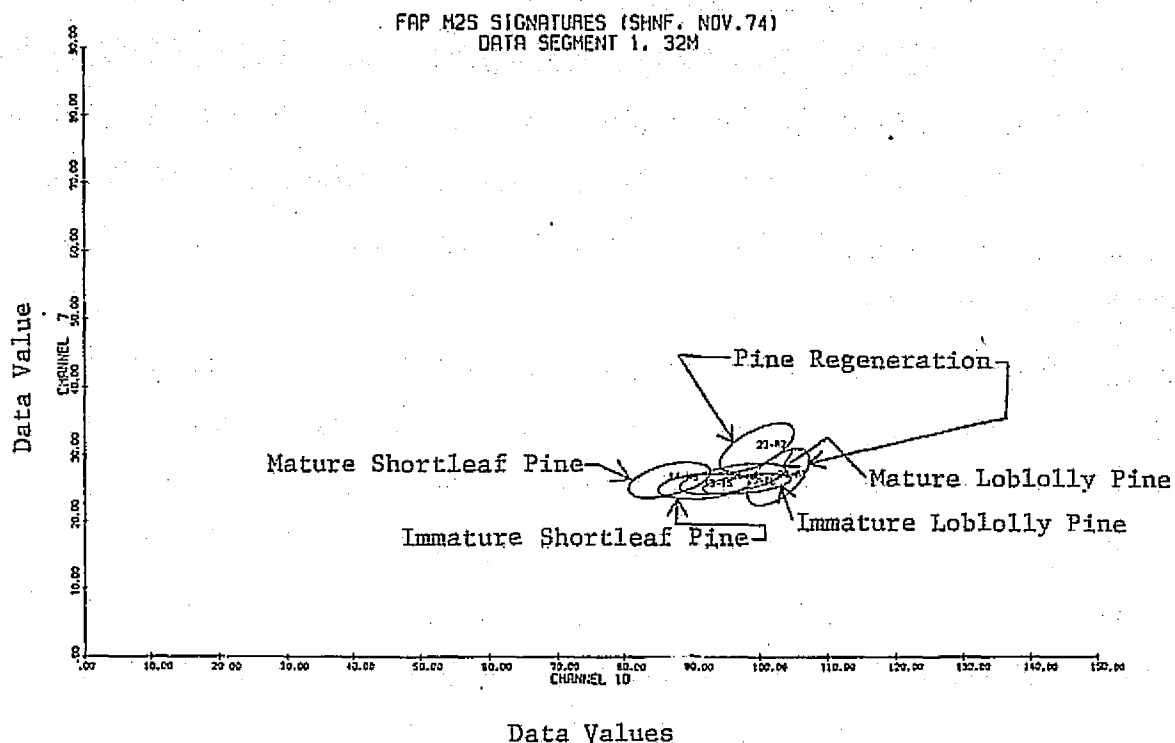
FIGURE 5.   SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 1 -- (32 METERS)^2 RESOLUTION

FRP M25 SIGNATURES (SHNF. NOV.74)
DATA SEGMENT 1. 64M
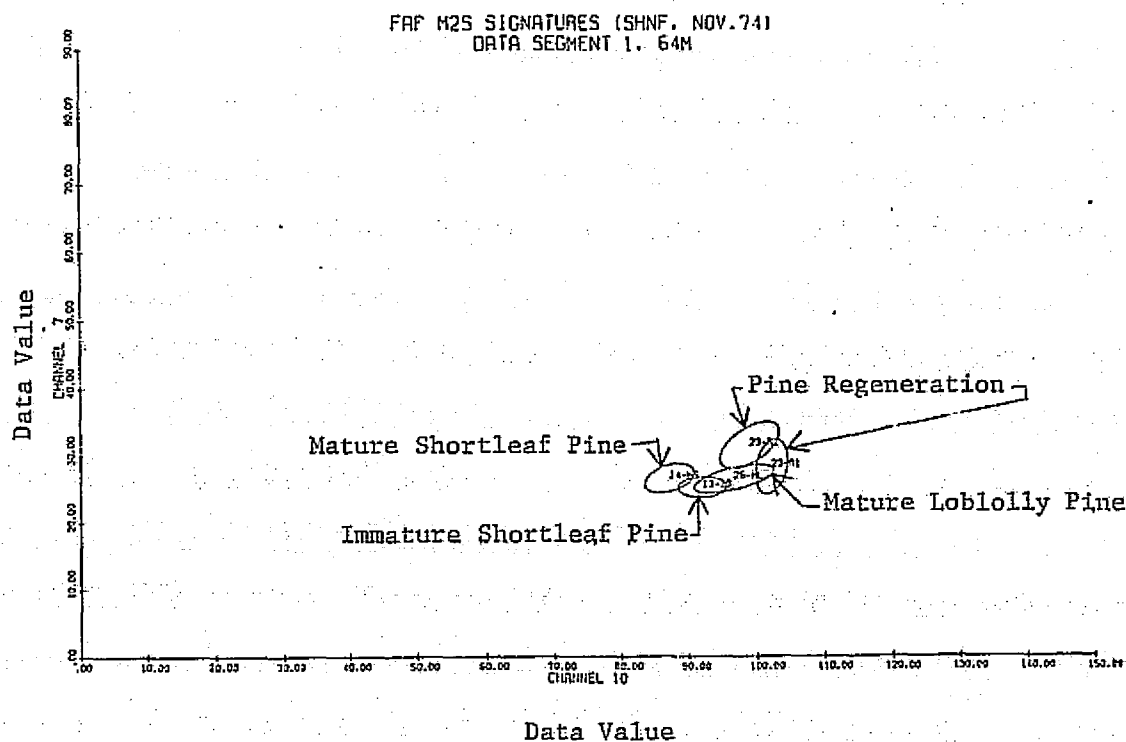
FIGURE 6.   SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 1 -- (64 METERS)^2 RESOLUTION

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FAP M2S SIGNATURES (SHNF, NOV.74)
DATA SEGMENT 2, 2M

Data Value

Cutover Land

Immature Laurel Oak/Willow Oak

Immature Sweetgum/ Nuttal Oak/Willow Oak

Immature Loblolly Pine

Data Value
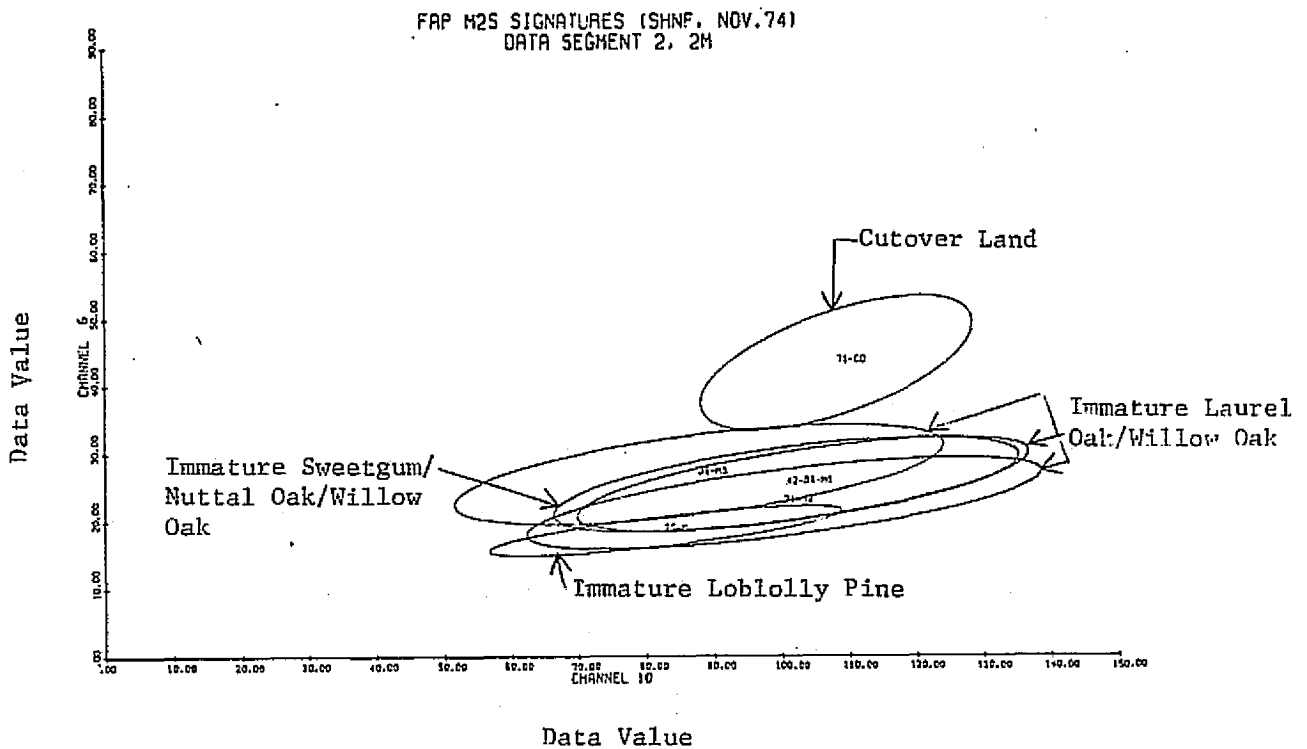
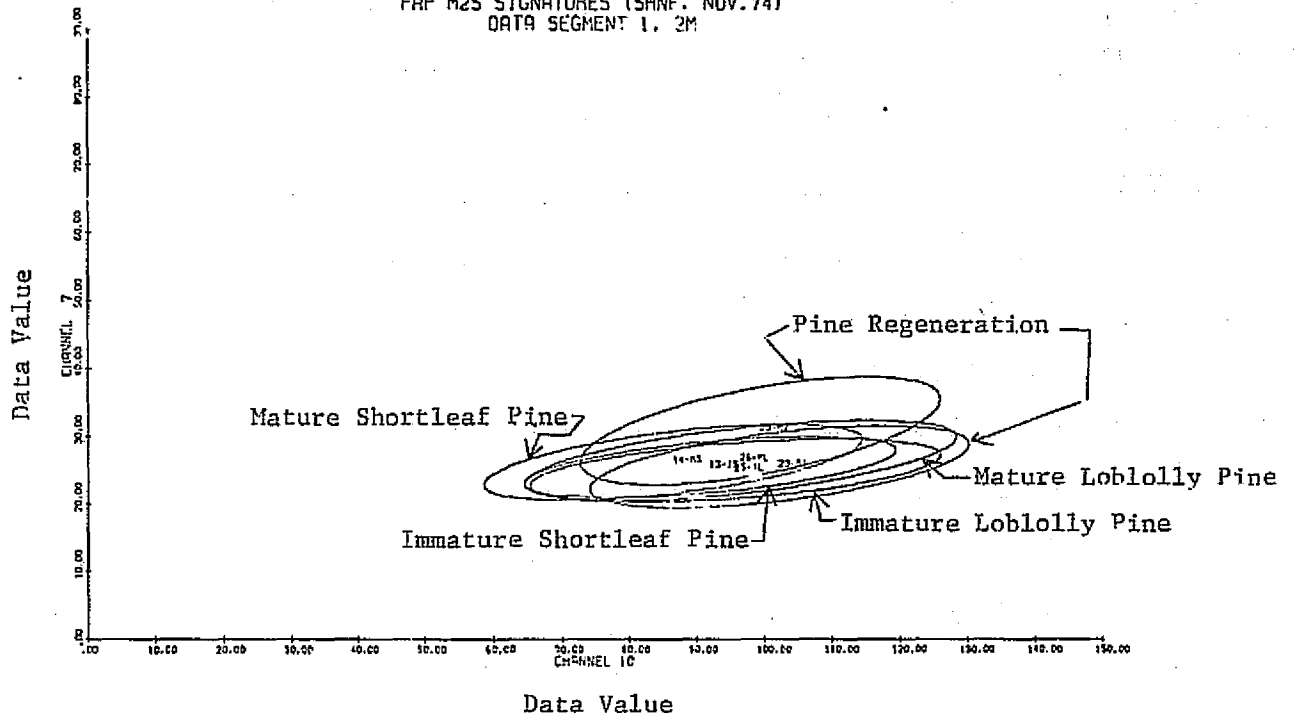FIGURE 7.   SIGNATURE DISTRIBUTION FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 2 -- (2 METERS)^2 RESOLUTION

FAP M2S SIGNATURES (SHNF, NOV.74)
DATA SEGMENT 2, 64M

Data Value
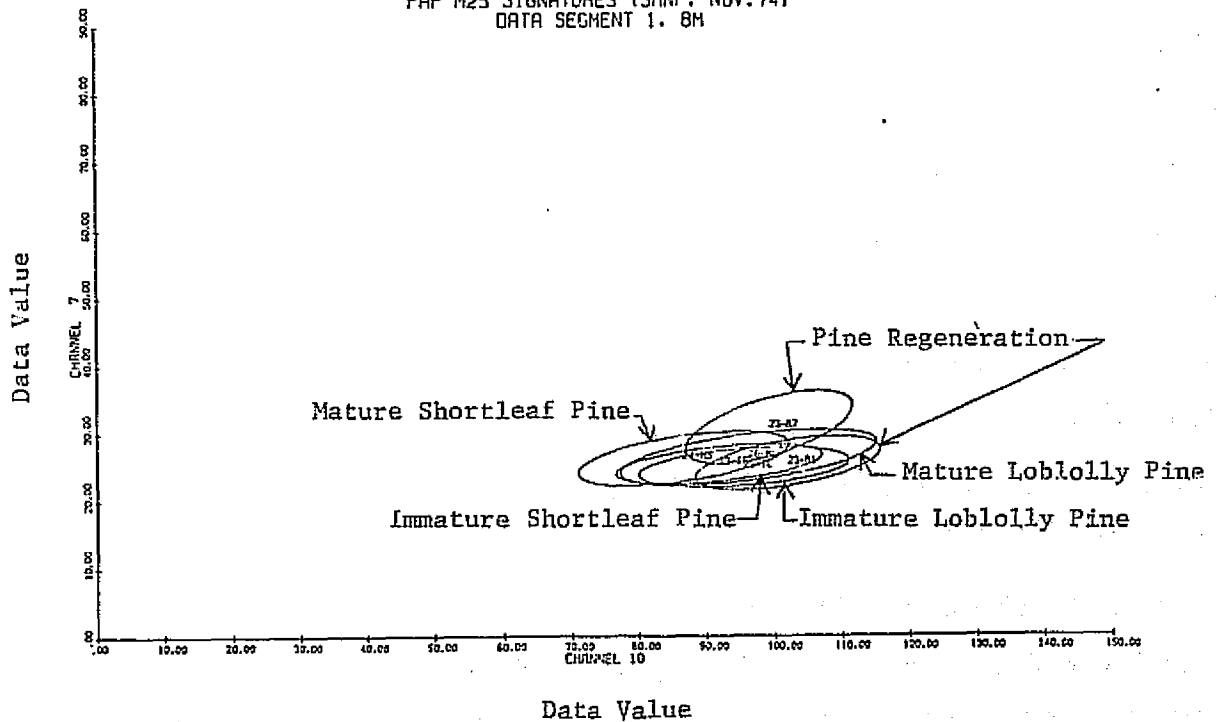
Cutover Land

Immature Laurel Oak/ Willow Oak

Immature Sweetgum/ Nuttal Oak/Willow Oak
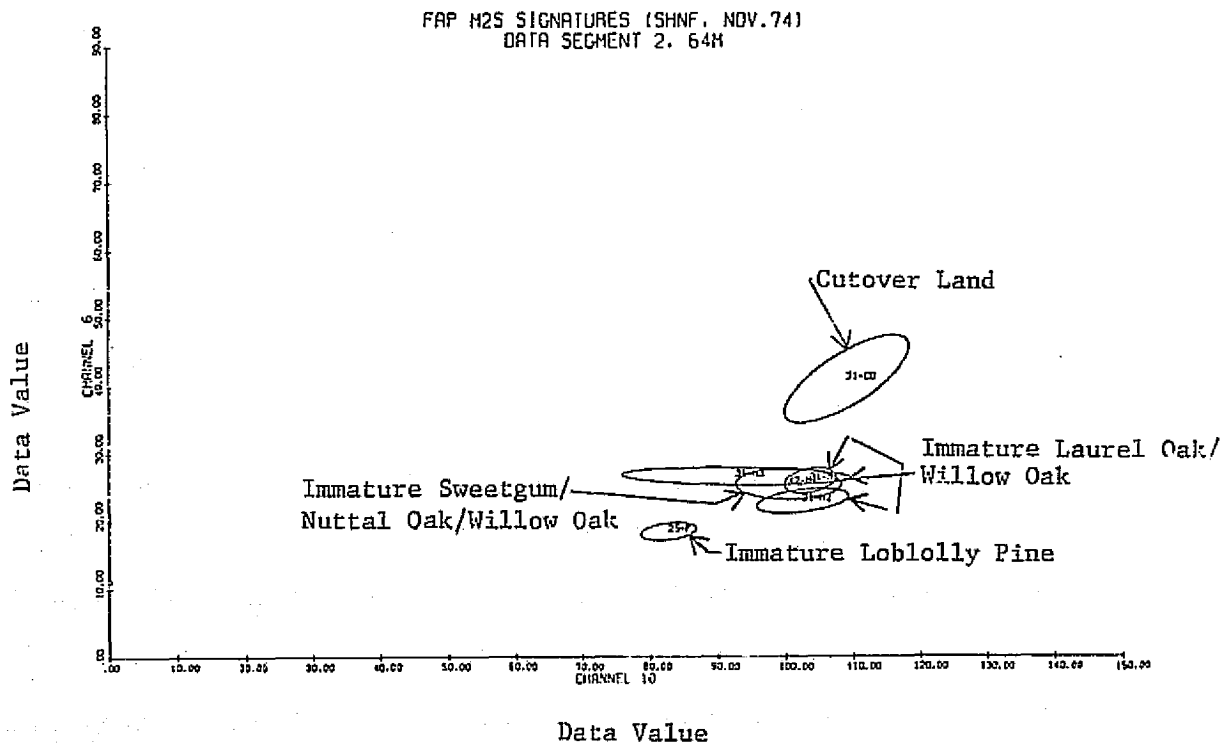
Immature Loblolly Pine

Data Value

FIGURE 8.   SIGNATURE DISTRIBUTIONS FOR CONDITION CLASS FEATURES OF DATA
SEGMENT 2 -- (64 METERS)^2 RESOLUTION

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illustrate feature signatures of Data Segment 2 at $(2)^2$ and $(64 \text{ meters})^2$.
A test of spectral channel performance for feature discrimination indi-
cated that the pairs of channels illustrated for each data segment
proved to be among the best for separating the respective features at
all cases of spatial resolution. However, the use of all 11 channels
when classifying the data values offered considerable improvement for
feature discrimination.

At $(2 \text{ meters})^2$, the largely overlapping signature distributions
in each data segment obviously offer the least likelihood for success-
ful discrimination of features. The large variance for each signature
provides evidence of the spectral irregularities within the training
areas, and the small mean separation among the signatures indicates
many similarities among the data values of resolution elements in all
training areas. Thus, misclassifications of those elements by the
resulting signature set will be high. As resolution is degraded, the
variance of each signature becomes smaller while the means for the
most part remain unchanged, causing the amount of statistical overlap
(competition) among the signatures to decrease. (Slight movement of
some means is evident and is attributed to the random noise that was
reinserted into the spatially degraded data.) Thus, resolution ele-
ments in coarser resolution data should have higher probabilities of
being correctly classified. The results of Ref. 1 indicated that
higher classification accuracies were indeed achieved when averaged
over all features and for some individual features.

The fact that classification accuracies for some features show a
different dependence on spatial resolution seems to be dependent on
the amount of competition existing between any one feature signature
and the signatures of other features. Figures 3-6 illustrate how the
amount of overlap decreases dramatically for some signatures and only
slightly, if at all, for others. Although all signatures represent

pine features, both a greater amount of illumated background mate-
rials seen among the small trees within the Pine Regeneration feature
and the somewhat larger proportion of shadows cast by the large conifer
(and occasional hardwood) tree crowns in the Mature Shorcleaf Pine
feature serve to displace the respective signature means for these
features away from the centroid of all the signatures. Thus the capa-
bility for accurate feature discrimination will be higher for these
signatures by virtue of encompassing some amount of unique decision
space. With decreasing variance for all signatures, feature discrimi-
nation for these signatures improves, since overlap with neighbor-
ing signatures decreases, thus enlarging their amount of unique deci-
sion space. Figure 9 illustrates, for Mature Shortleaf Pine, the pro-
gressive decrease in the misclassification of its resolution elements
as spatial resolution was degraded.

However, physical appearances for Immature Shortleaf Pine and
Immature Loblolly Pine are less differentiable, and the increased
proportion of hardwood tree crowns within the Mature Loblolly Pine
feature results in a larger variance for this signature. The near
co-location of these signature means with the centroid for all the
signatures results in considerable overlap between each of these
signatures and its neighbors that continues to exist despite a pro-
gressive decrease in variance. Note that the signature for Immature
Loblolly Pine seems to have an advantage at feature discrimination
(see Figure 1) due to its relatively smaller variance, while the larger
variance for the Mature Loblolly Pine signature detracts greatly from
its feature discrimination capability. Figure 10 illustrates a consid-
erable amount of misclassification for resolution elements within the
Mature Loblolly Pine feature at all cases of spatial resolution. In
Figure 6, the removal of the Immature Loblolly Pine signature at
$(64 \text{ meters})^2$ serves to reduce much of the competition for Immature
Loblolly Pine, thus, apparently causing the dramatic improvement in the
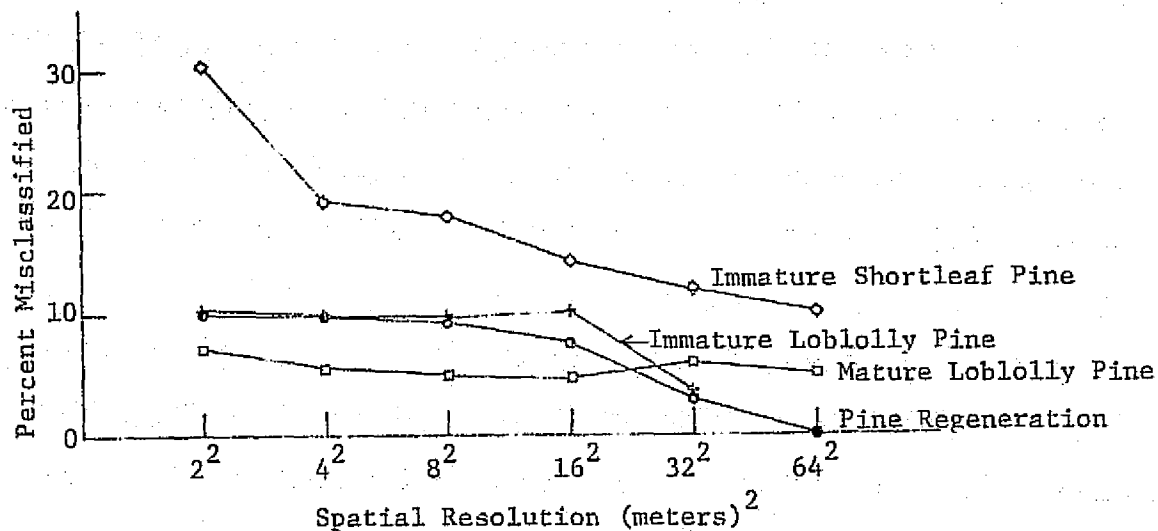classification accuracy illustrated for these two features in Figure 1.

FIGURE 9. PERCENT OF RESOLUTION ELEMENTS WITHIN THE MATURE SHORTLEAF
PINE FEATURE THAT WERE MISCLASSIFIED AS EACH OF THE REMAINING
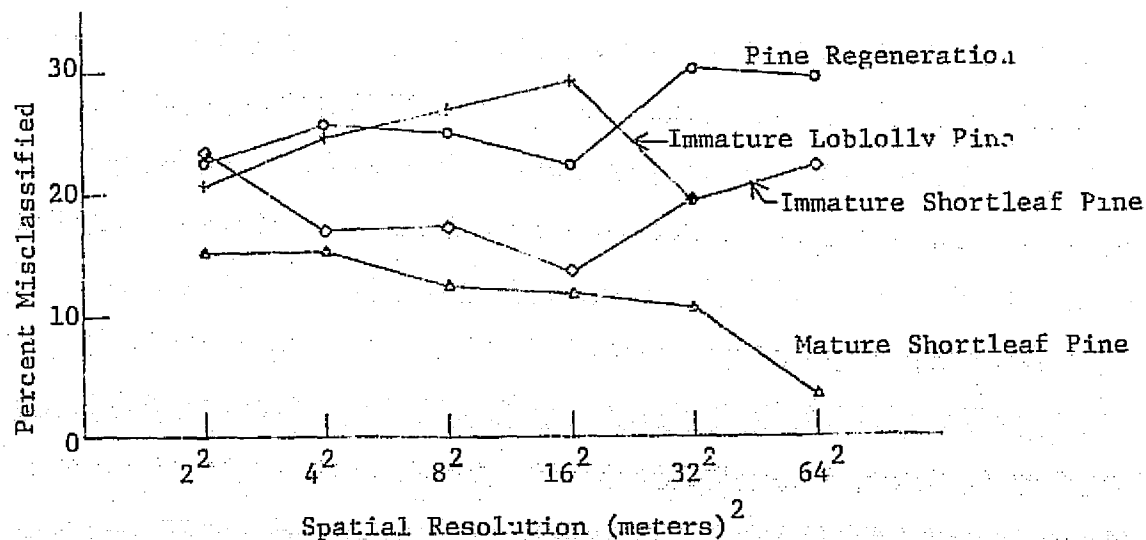FEATURES IN DATA SEGMENT 1

FIGURE 10. PERCENT OF RESOLUTION ELEMENTS WITHIN THE MATURE LOBLOLLY
PINE FEATURE THAT WERE MISCLASSIFIED AS EACH OF THE REMAINING
FEATURES IN DATA SEGMENT 2

The fact that classification performance does generally increase for all features in Data Segment 2 is apparently due to the greater mea. s~paration among the feature signatures (Figures 7 and 8) — a result of the more readily differentiable feature appearances. It is therefore likely that overlap among the resultant signature distributions was less severe, thus allowing each distribution to encompass some amount of unique decision space. Decreases in variance caused by degrading spatial resolution would act to reduce overlap and further enlarge the unique decision space for each signature.

Note that the use of two signatures to classify the Pine Regeneration Feature in Data Segment 1 and three signatures to classify Immature Laurel Oak/Willow Oak Sawtimber in Data Segment 2 likely influenced their relatively high classification performances demonstrated in Figures 1 and 2. Such use of multiple signatures to account for obvious nonuniform areas within the feature resulted in signature distributions having smaller variances than would have occurred for a single signature extracted from the same training area as for the multiple signatures. Thus, for regions of statistical overlap with neighboring signatures of larger variance, these signatures displayed an improved ability for classifying their respective features since misclassifications of respective resolution elements were lower.

2.3.2 Simulation and Analysis of Signature Statistics

The classification results displayed in Figures 1 and 2 were obtained with a standard single-element classification algorithm that utilizes signatures having multivariate normal statistics. To the extent that the data actually were normally distributed, one should be able to match the actual classification performance with a similar classification of simulated data generated from the signature statistics under an assumption of multivariate normality. The simulation results, thus, represent an ideal performance level to be expected under the normality assumption.

Departures of real results from the simulated results then would be attributable to non-normal distributions of data values within the feature training areas.

Results obtained for the ideal expected classification performance of each data segment generally displayed great similarities to the real classification performances illustrated in Figures 1 and 2. Figure 11 illustrates the ideal expected classification performance for features of Data Segment 1 at each case of spatial resolution. Figure 12 shows the difference between the ideal expected performance and real performance expressed as the root mean square (RMS) error in percent accuracy between each feature's real classification performance and its ideal expected classification performance over all features in each data segment. The existence of error indicates some deviation from true normal distributions does exist for the data values within the training areas. The general decrease in error as spatial resolution degrades suggests that the data values within the training areas tend to approach a normal distribution more closely as the ground area of each resolution element increases. This is not surprising since an increased amount of ground area within a resolution element would tend to average out variations caused by the spectral irregularities within a feature area and reduce the likelihood of different modes that might occur within distributions of fine resolution data.

To illustrate the effect of degrading spatial resolution on signature variance, we have plotted the values of determinants for signatures from Data Segment 1 in Figure 13. Each determinant represents the product of the signature eigenvalues and thus, is proportional to the square of the multi-dimensional dispersion volume of the signature distribution. A large decrease in determinant value indicates a large reduction in "signature size".

It is interesting to note that the determinants for various signatures do not necessarily decrease at the same rate, as resolution degrades.
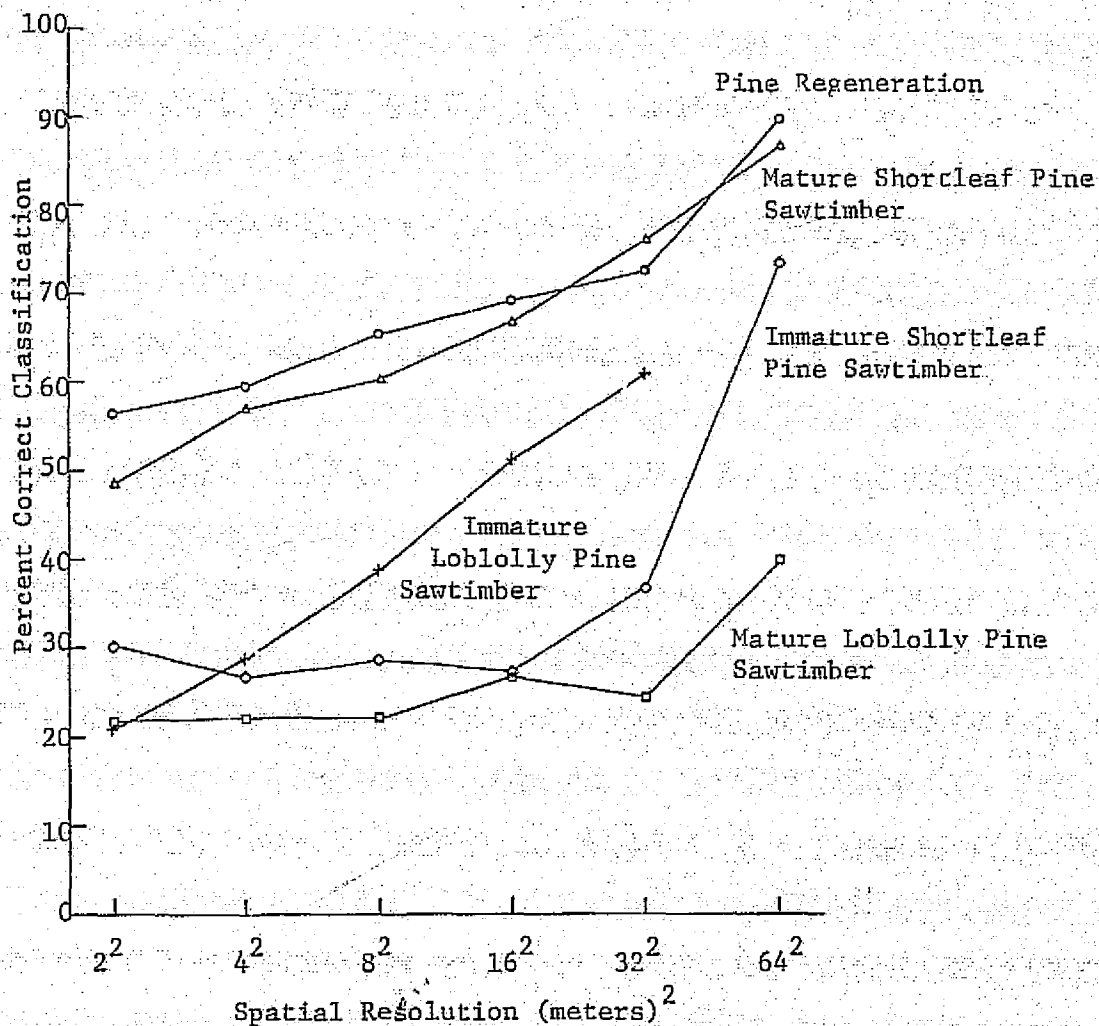
FIGURE 11. IDEAL CLASSIFICATION ACCURACIES TO BE EXPECTED FOR DATA SEG-
MENT 1 ASSUMING THAT THE DATA VALUES WITHIN FEATURE TRAINING
AREAS HAD MULTIVARIATE NORMAL DISTRIBUTIONS AT EACH
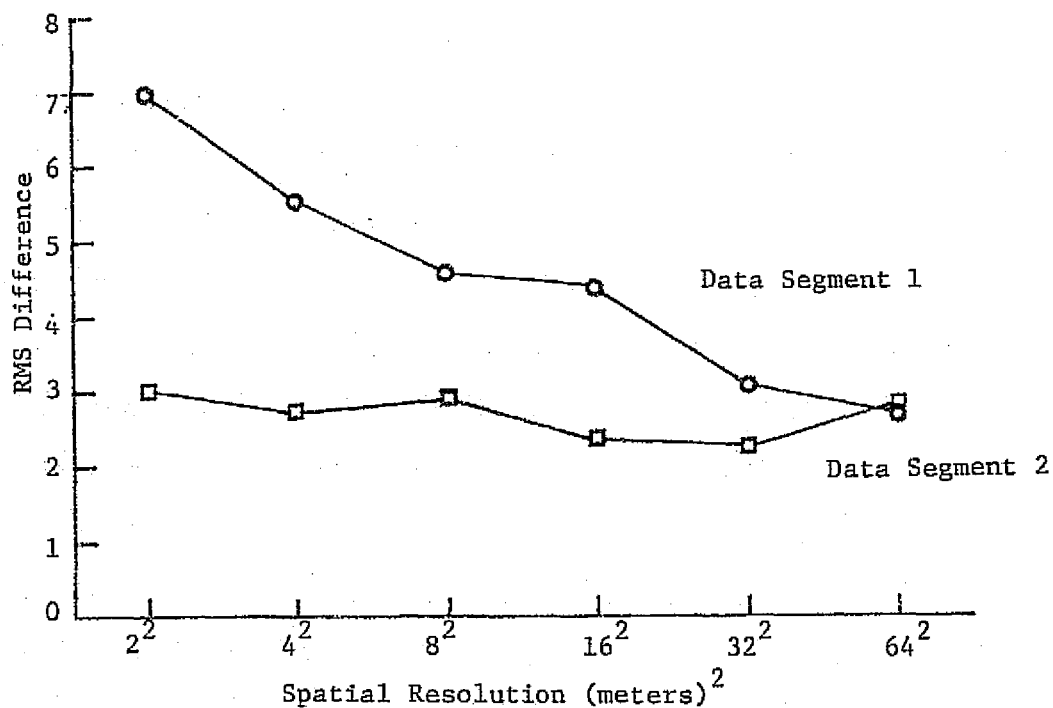CASE OF SPATIAL RESOLUTION

FIGURE 12. RMS DIFFERENCE OVER ALL FEATURES IN PERCENT ACCURACY BETWEEN
THE REAL AND IDEAL EXPECTED CLASSIFICATION PERFORMANCE
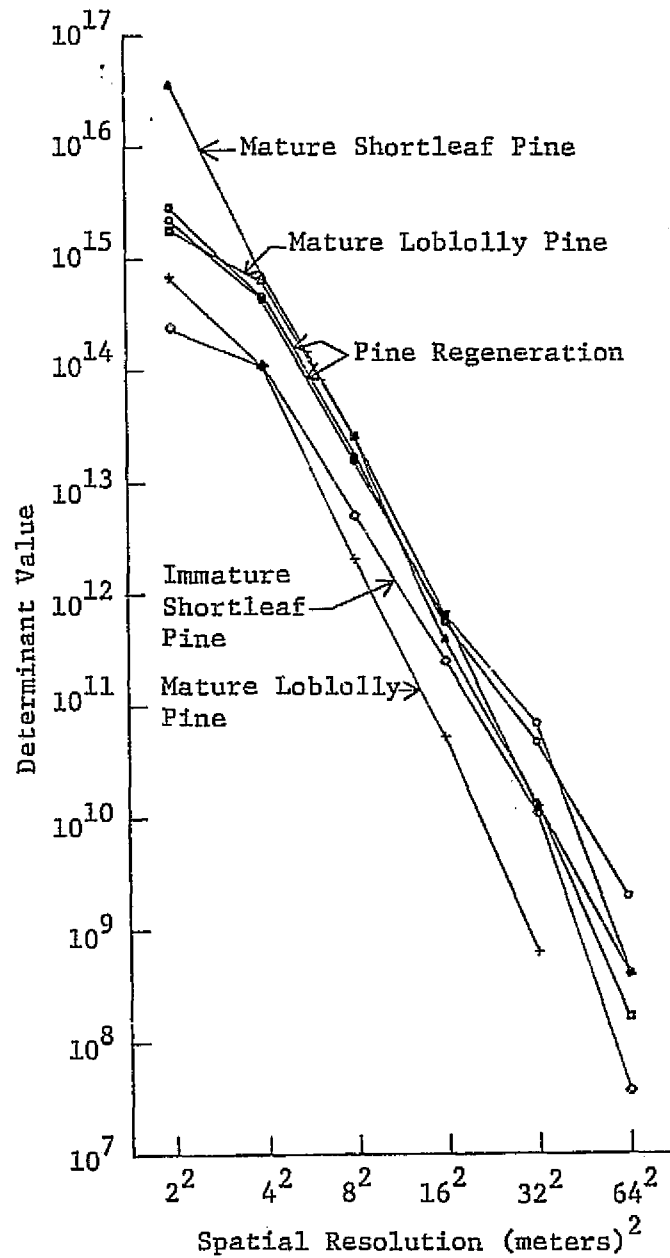FOR EACH DATA SEGMENT

FIGURE 13, DETERMINANTS FOR SIGNATURES OF DATA SEGMENT 1 AS A FUNCTION OF SPATIAL RESOLUTION

For this set of signatures, the decrease in absolute magnitude for any signature determinant is very large for each succesive change in resolution, but differences in the rates of decrease among signatures, although small, are evident. We suggest that such non-uniform rates of change in determinant value may be indicative of some textural attribute that varies with spatial resolution.

A further but inconclusive observation is provided by Figure 14, where, for each of two feature signatures, the square root of the determinant is compared to the product of the 11 channel standard deviations. This latter quantity is proportional to the multi-dimensional volume that would be occupied by a totally uncorrelated multivariate signature distribution. The actual hypervolume occupied by a distribution (proportional to the square root of the determinant) is less by virtue of the correlation that exists between channels. As spatial resolution degrades, the square root of the determinant decreases less than the product of the standard deviations, and therefore approaches that quantity. This indicates that the correlations between channels decrease as resolution is degraded.
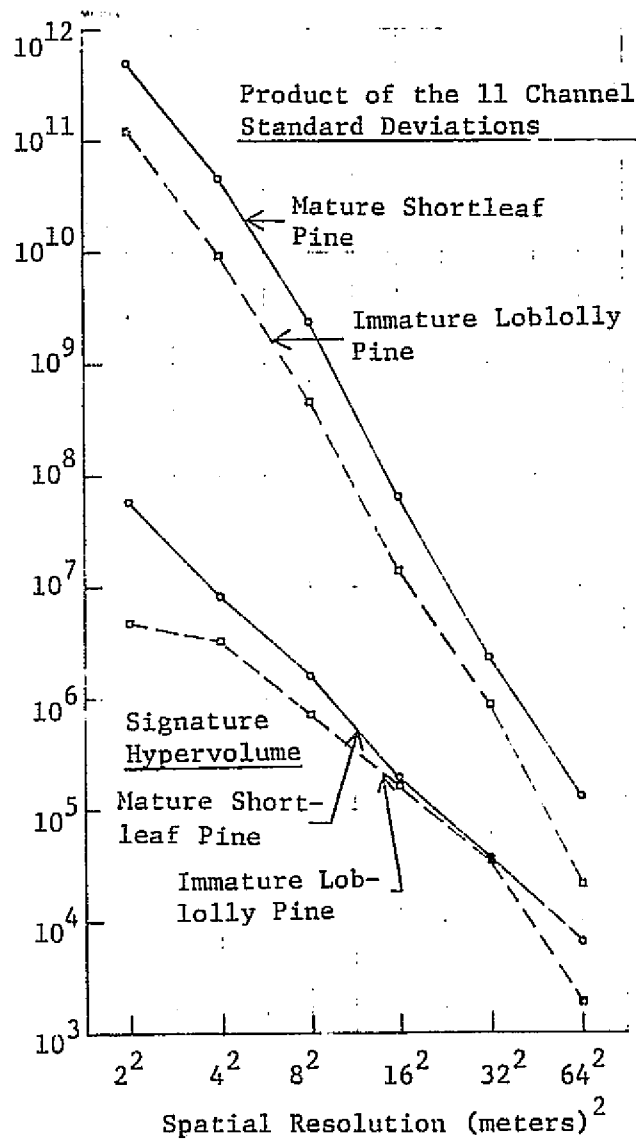
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FIGURE 14. COMPARISON OF SIGNATURE HYPERVOLUMES WITH THE RESPECTIVE
PRODUCTS OF THE 11 CHANNEL STANDARD DEVIATIONS

3

INVESTIGATION OF DECISION THRESHOLD EFFECTS

3.1 BACKGROUND

Figures 15 and 16 show the percent of unclassified resolution elements as a function of spatial resolution that were previously reported [1] for Data Segment 1 and Data Segment 2, respectively. These results had been obtained by using a standard single-element classification algorithm that incorporated a constant decision rejection threshold for all cases of spatial resolution. Figure 15 indicates that the percent of unclassified elements in Data Segment 1 is fairly constant except when resolution size is $(32 \text{ meters})^2$ and $(64 \text{ meters})^2$. For Data Segment 2, only the $(64 \text{ meters})^2$ case of resolution has a level of unclassified elements which is inconsistent with the other resolutions.

3.2 PROCEDURE

To investigate the effect of the classification rejection threshold for influencing the amount of unclassified resolution elements, we reclassified the data for the three cases of spatial resolution (as indicated above) having large proportions of unclassified elements. Each data set was reclassified using no rejection threshold so that each element was forced to be classified as one of the forest features. The exponent of the multivariate normal density associated with the classification of each element was preserved, and the classification results were tabulated for the exponent level which yielded approximately two percent unclassified elements for Data Segment 1 on boundary inclusive test sets. For Data Segment 2, the exponent level was adjusted to yield 4.5 percent unclassified elements matching the other resolutions for that segment.

3.3 RESULTS

Figures 17 and 18 show the percent of unclassified elements as a function of spatial resolution, using threshold-adjusted classification results. Since the threshold was adjusted to provide a constant
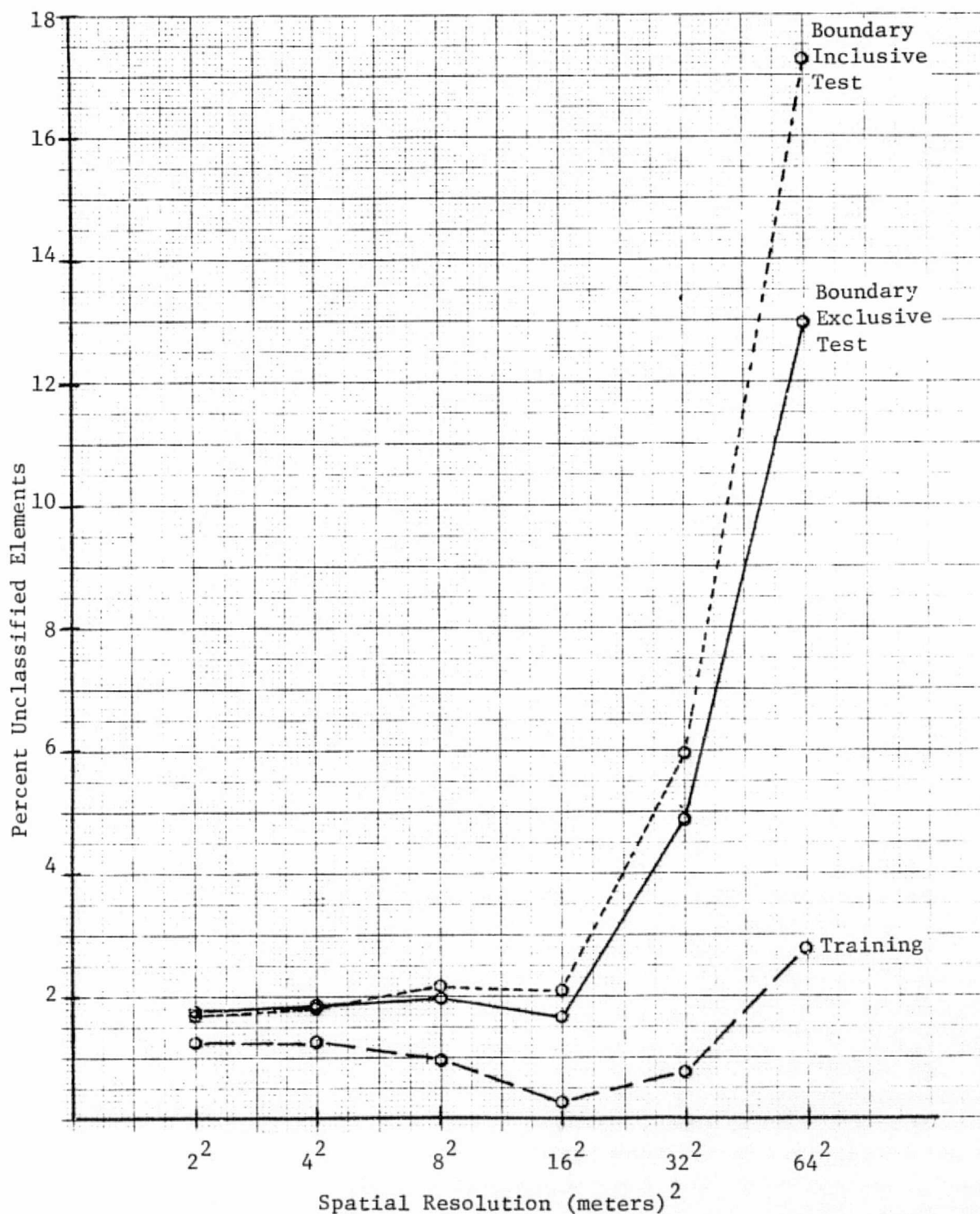
FIGURE 15. PERCENT OF ELEMENTS IN DATA SEGMENT 1 WHICH ARE UNCLASSIFIED
WITH THE THRESHOLD CONSTANT AS SPATIAL RESOLUTION VARIES
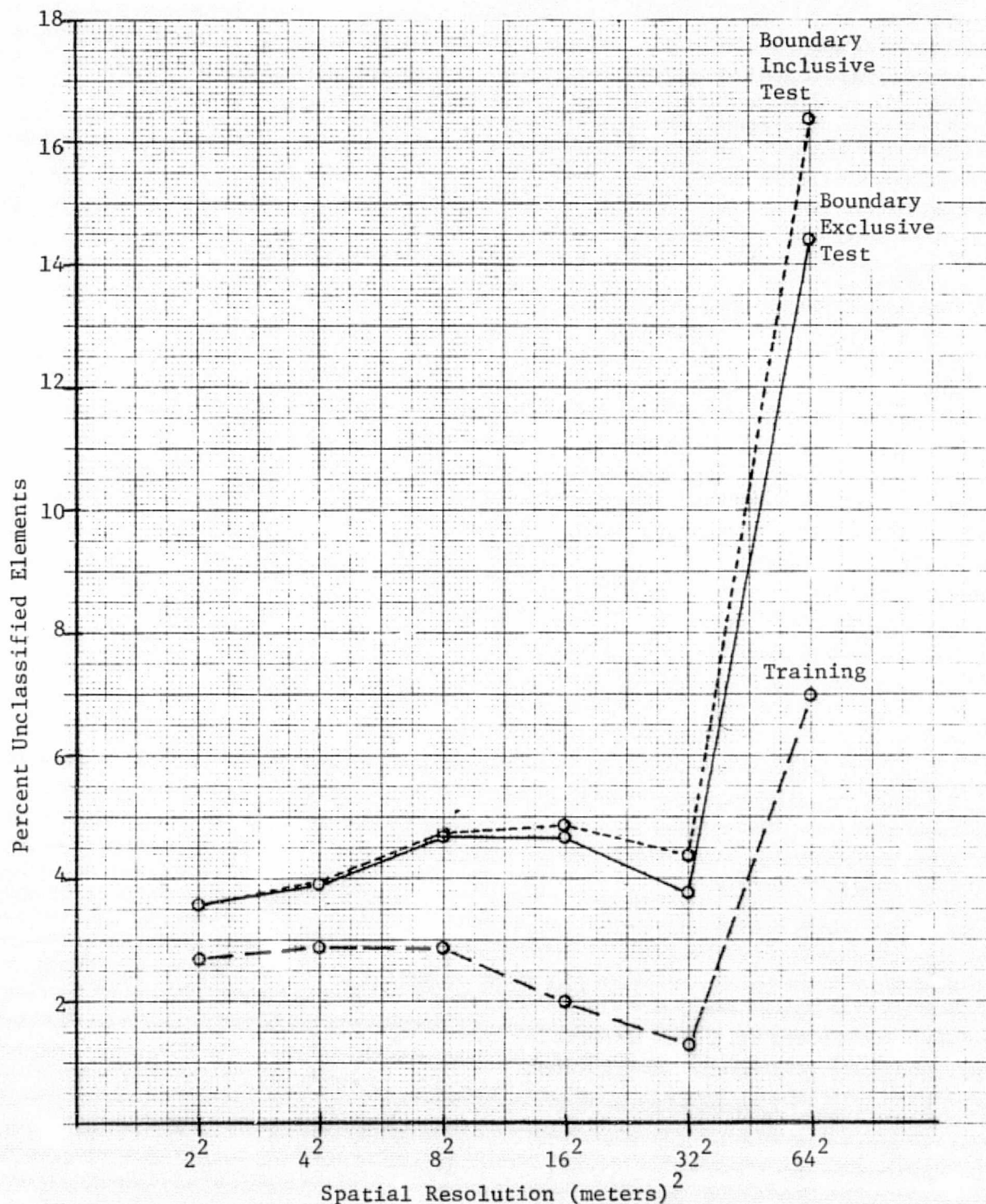
FIGURE 16. PERCENT OF ELEMENTS IN DATA SEGMENT 2 WHICH ARE UNCLASSIFIED
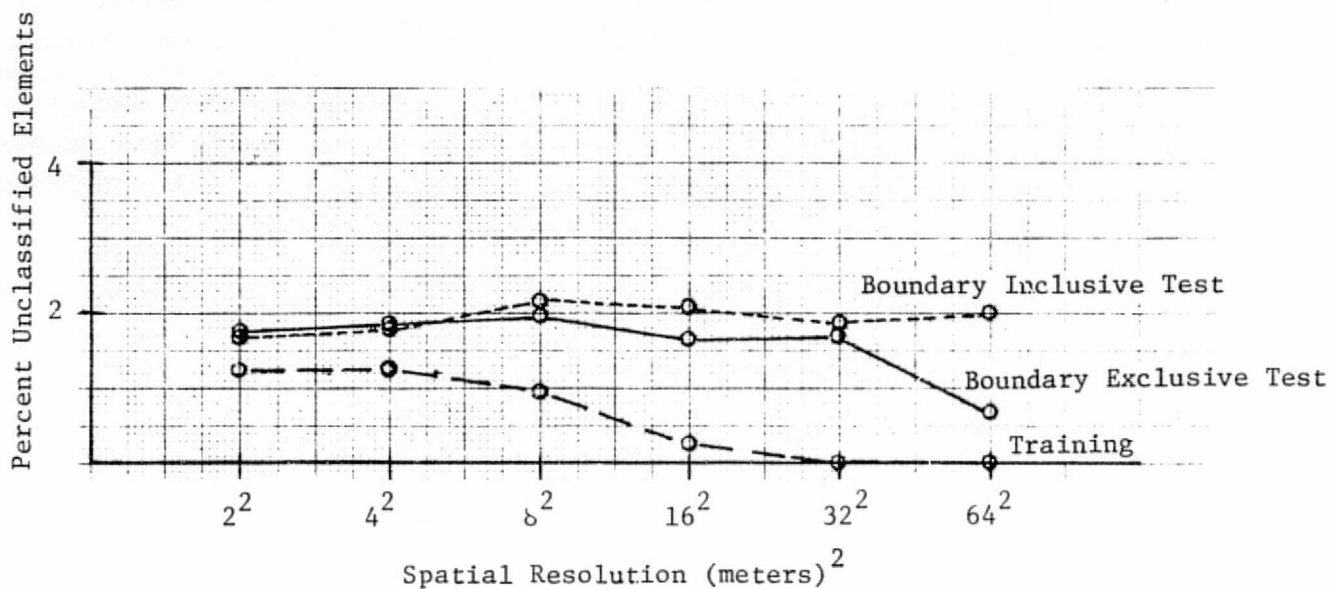WITH THE THRESHOLD CONSTANT AS SPATIAL RESOLUTION VARIES

FIGURE 17. PERCENT OF ELEMENTS IN DATA SEGMENT 1 WHICH ARE UNCLASSIFIED
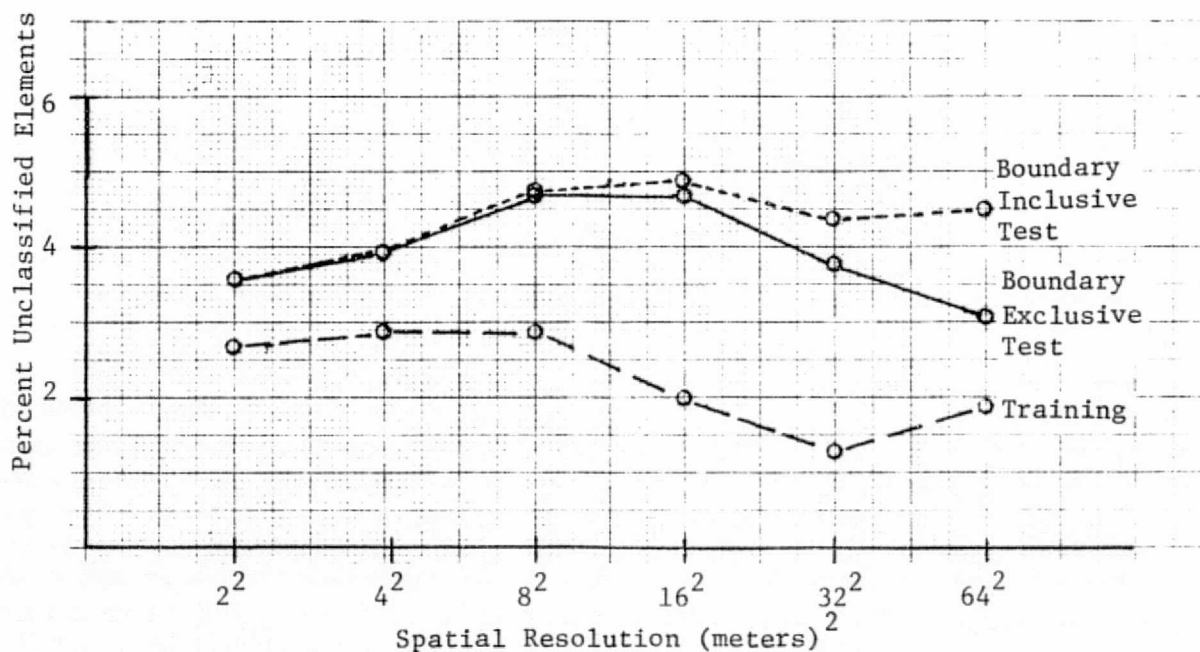AS SPATIAL RESOLUTION VARIES WHEN THE THRESHOLDS ARE ADJUSTED

FIGURE 18. PERCENT OF ELEMENTS IN DATA SEGMENT 2 WHICH ARE UNCLASSIFIED
AS SPATIAL RESOLUTION VARIES WHEN THE THRESHOLDS ARE ADJUSTED

proportion of unclassified elements in boundary inclusive test sets as
spatial resolution varied, these test sets show little variance as a
function of spatial resolution. Training sets and boundary exclusive
test sets, which were classified using the threshold determined for
boundary inclusive test sets, also now exhibit fairly consistent propor-
tions of unclassified elements for all spatial resolutions.

The previously used threshold level (chi square value), which gives
a 0.001 level of significance for 11 channel data, was 31. For Data Seg-
ment 1 levels for the threshold adjusted classifications were raised to
52 for $(32 \text{ meters})^2$ and 128 for $(64 \text{ meters})^2$. The $(64 \text{ meters})^2$ Data Seg-
ment 2 classification required a threshold level increase to 55 to give a
proportion of unclassified elements consistent with the other cases of
spatial resolution.

Results are reported comparing the threshold-adjusted classifications
to previous classifications using the 31 threshold level. The effects
of these results on both classification accuracy and area proportion
estimation are discussed.

3.3.1 INFLUENCE ON FEATURE AND HIERARCHY CLASSIFICATION ACCURACY

The comparison of classification results using different threshold
levels for $(32)^2$ and $(64 \text{ meters})^2$ spatial resolutions of Data Segment 1
are given in Tables 1-3 for training sets, boundary exclusive test sets
and boundary inclusive test sets, respectively. The percent correct
classification is reported for each of the forest features in the
respective hierarchies and the overall percent correct classification
accuracy, based on total number of points correctly classified in the
data segment, has also been calculated for each hierarchy.

Training set classification accuracies (Table 1) remain the same
or improve only slightly with the higher threshold levels for both cases
of spatial resolution. This slight change is not surprising since
Figure 15 shows that the percent of unclassified elements for training
sets was small when the previous threshold levels were used.

TABLE 1. COMPARISON OF PERCENT CORRECT CLASSIFICATION FOR $(32)^2$ AND $(64 \text{ METERS})^2$ TRAINING SETS IN DATA SEGMENT 1 USING CONSTANT THRESHOLDS VERSUS ADJUSTED THRESHOLDS

	$(32M)^2$		$(64M)^{2*}$	
	Constant Threshold (31)	Adjusted Threshold (52)	Constant Threshold (31)	Adjusted Threshold (128)
HIERARCHY: CONDITION CLASS				
CONIFER REGEN. (2.3)	70.5	70.5	87.3	90.1
LOBLOLLY - IMM. (2.5)	65.2	65.2	---	---
LOBLOLLY - MATURE (2.6)	19.6	19.6	44.4	44.4
SHORTLEAF - IMM. (1.3)	35.6	35.6	71.4	71.4
SHORTLEAF - MATURE (1.4)	75.6	75.6	85.0	85.0
OVERALL	57.4	57.4	76.9	78.0
HIERARCHY: GROWTH STAGE				
CONIFER REGEN. (2.3)	70.5	70.5	87.3	90.1
IMM. SAWTIMBER	60.6	61.9	65.1	65.1
MATURE SAWTIMBER	62.2	62.2	71.6	73.1
OVERALL	65.1	65.4	76.2	77.9
HIERARCHY: COVER TYPE				
CONIFER REGEN. (2.3)	70.5	70.5	87.3	90.1
SHORTLEAF PINE	75.0	75.0	90.7	90.7
LOBLOLLY PINE	44.8	44.8	45.7	45.7
OVERALL	67.8	67.8	80.7	81.8
HIERARCHY: PHYSIOGNOMY				
CONIFER REGEN. (2.3)	70.5	70.5	87.3	90.1
PINE SAWTIMBER	88.0	88.5	90.9	91.8
OVERALL	81.2	81.5	89.5	91.2

---

*The $(64 \text{ meters})^2$ data set did not contain a signature for Immature Loblolly Pine (2.5).

Comparison of Figure 11 with Figure 15 indicates that the more dramatic decreases in unclassified elements occurred when the higher threshold levels were used with the test sets, especially for the $(64 \text{ meters})^2$ case. Test set classification results (Tables 2 and 3) show slightly improved overall accuracies for the $(32 \text{ meters})^2$ case of spatial resolution, and the $(64 \text{ meters})^2$ case displays even more dramatic increases in the overall accuracies, ranging from 7.8 percentage points for condition class in boundary exclusive test sets to 13.0 percentage points for physiognomy in the boundary inclusive test sets.

Table 4 compares the classification accuracies for individual forest features as well as the calculated overall accuracy of training sets and test sets in Data Segment 2, using the two different threshold levels for the $(64 \text{ meters})^2$ case. Training set overall classification accuracies improve by approximately four percentage points, but again the test sets show greater increases, i.e., 9 to 10 percentage points, in overall accuracies.

The larger increases in test sets can be explained by a comparison of Figures 16 and 18. Figure 16 shows that test sets contained a larger proportion of unclassified elements than training sets in the original classification. Thus, when the higher threshold level was used (Figure 18), test sets show a greater decrease in the proportion of unclassified elements than training sets.

Overall classification accuracies for each hierarchy of features in Data Segments 1 and 2 are plotted as a function of spatial resolution in Figures 19-24. Each figure contains four plots. Plot (a) compares the overall accuracy for training, boundary exclusive test, and boundary inclusive test sets when the proportion of unclassified elements remains constant for all cases of spatial resolution. The other three plots, (b)-(d), show for each type of data set the differences between these classification accuracies and those obtained using a constant threshold level.

TABLE 2.   COMPARISON OF PERCENT CORRECT CLASSIFICATION FOR $(32)^2$ AND
$(64 \text{ METERS})^2$ BOUNDARY EXCLUSIVE TEST SETS IN DATA SEGMENT 1
USING CONSTANT THRESHOLDS VERSUS ADJUSTED THRESHOLDS

	$(32\text{M})^2$		$(64\text{M})^{2*}$	
	Constant Threshold (31)	Adjusted Threshold (52)	Constant Threshold (31)	Adjusted Threshold (128)
HIERARCHY: CONDITION CLASS				
CONIFER REGEN. (2.3)	71.4	73.2	78.6	90.5
LOBLOLLY - IMM. (2.5)	56.8	56.8	---	---
LOBLOLLY - MATURE (2.6)	19.4	19.9	31.0	38.1
SHORTLEAF - IMM. (1.3)	31.6	31.8	39.5	44.4
SHORTLEAF - MATURE (1.4)	73.0	73.0	82.1	82.1
OVERALL	52.2	53.0	59.9	67.7
HIERARCHY: GROWTH STAGE				
CONIFER REGEN. (2.3)	71.4	73.2	78.6	90.5
IMM. SAWTIMBER	53.5	55.8	40.2	44.8
MATURE SAWTIMBER	54.2	54.7	59.3	65.4
OVERALL	60.7	62.3	61.9	70.1
HIERARCHY: COVER TYPE				
CONIFER REGEN. (2.3)	71.4	73.2	78.6	90.5
SHORTLEAF PINE	67.0	67.9	80.0	84.2
LOBLOLLY PINE	42.4	44.4	33.3	39.6
OVERALL	64.6	66.0	71.8	79.6
HIERARCHY: PHYSIOGNOMY				
CONIFER REGEN. (2.3)	71.4	73.2	78.6	90.5
PINE SAWTIMBER	82.8	85.3	80.4	88.7
OVERALL	78.3	80.6	79.6	89.5

---

*The $(64 \text{ meters})^2$ data set did not contain a signature for Immature Loblolly Pine (2.5).

TABLE 3. COMPARISON OF PERCENT CORRECT CLASSIFICATION FOR $(32)^2$ AND $(64 \text{ METERS})^2$ BOUNDARY INCLUSIVE TEST SETS IN DATA SEGMENT 1 USING CONSTANT THRESHOLDS VERSUS ADJUSTED THRESHOLDS

	$(32M)^2$		$(64M)^{2*}$	
	Constant Threshold (31)	Adjusted Threshold (52)	Constant Threshold (31)	Adjusted Threshold (128)
HIERARCHY: CONDITION CLASS				
CONIFER REGEN. (2.3)	70.1	72.2	76.3	91.3
LOBLOLLY – IMM. (2.5)	47.1	48.5	---	---
LOBLOLLY – MATURE (2.6)	17.4	17.8	34.6	40.4
SHORTLEAF – IMM. (1.3)	28.9	29.1	29.3	35.3
SHORTLEAF – MATURE (1.4)	73.7	74.1	74.1	79.3
OVERALL	50.1	51.2	54.3	63.5
HIERARCHY: GROWTH STAGE				
CONIFER REGEN. (2.3)	70.1	72.2	76.3	91.3
IMM. SAWTIMBER	48.5	50.6	28.5	34.6
MATURE SAWTIMBER	53.8	54.4	58.2	65.5
OVERALL	58.2	59.9	55.8	65.8
HIERARCHY: COVER TYPE				
CONIFER REGEN. (2.3)	70.1	72.2	76.3	91.3
SHORTLEAF PINE	67.8	70.1	70.7	80.5
LOBLOLLY PINE	40.3	42.6	37.9	42.4
OVERALL	63.7	66.0	67.5	78.5
HIERARCHY: PHYSIOGNOMY				
CONIFER REGEN. (2.3)	70.1	72.2	76.3	91.3
PINE SAWTIMBER	81.3	84.9	72.1	83.8
OVERALL	77.1	80.1	73.8	86.8

---

[*]The $(64 \text{ meters})^2$ data set did not contain a signature for Immature Loblolly Pine (2.5).

TABLE 4. COMPARISON OF PERCENT CORRECT CLASSIFICATION FOR $(32)^2$ AND $(64 \text{ METERS})^2$ CASES IN DATA SEGMENT 2 USING CONSTANT THRESHOLDS VERSUS ADJUSTED THRESHOLDS
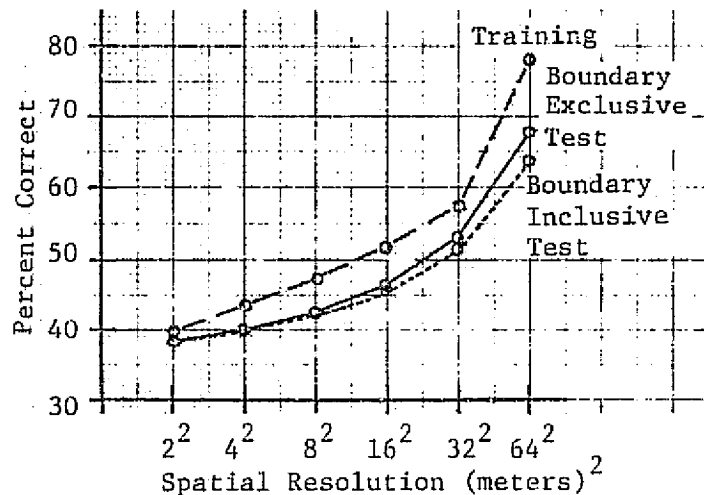
	TRAINING SETS		BOUNDARY EXCLUSIVE TEST SETS		BOUNDARY INCLUSIVE TEST SETS	
	Constant Threshold (31)	Adjusted Threshold (55)	Constant Threshold (31)	Adjusted Threshold (55)	Constant Threshold (31)	Adjusted Threshold (55)
HIERARCHY: CONDITION CLASS						
LOBLOLLY – IMM. (2.5)	100.0	100.0	86.0	90.0	72.9	80.0
LAUREL OAK/WILLOW OAK (3.1)	86.8	92.6	62.1	72.4	59.7	68.4
SWT GUM/N. OAK/W. OAK (4.2)	48.1	49.4	50.0	50.0	50.0	50.0
CUT OVER (7.1)	95.8	100.0	75.4	90.2	74.2	87.6
OVERALL 1*	76.3	79.1	69.3	79.2	64.9	73.9
OVERALL 2**	92.6	96.3				
HIERARCHY: PHYSIOGNOMY						
CONIFER SAWTIMBER (2.5)	100.0	100.0	86.0	90.0	72.9	80.0
HARDWOOD SAWTIMBER	89.8	95.2	84.3	94.1	85.5	94.5
CUT OVER (7.1)	95.8	100.0	75.4	90.2	74.2	87.6
OVERALL	92.6	96.7	82.6	92.4	80.5	90.2

*1 Overall calculated over all sets.

**2 Overall calculated omitting 4.2 training set.

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(a) Revised Results For All Data Sets
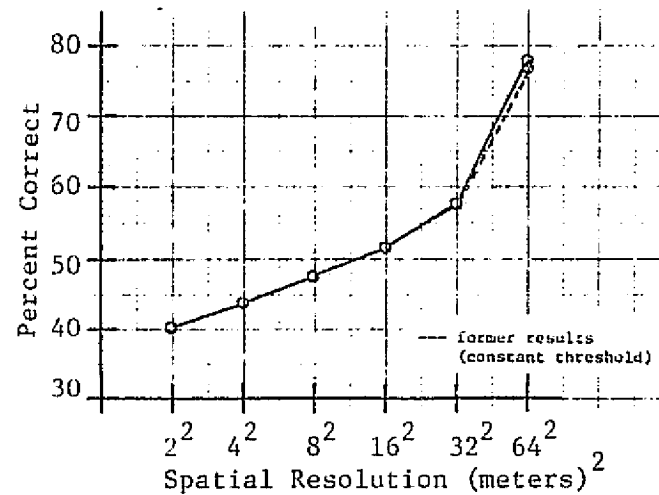
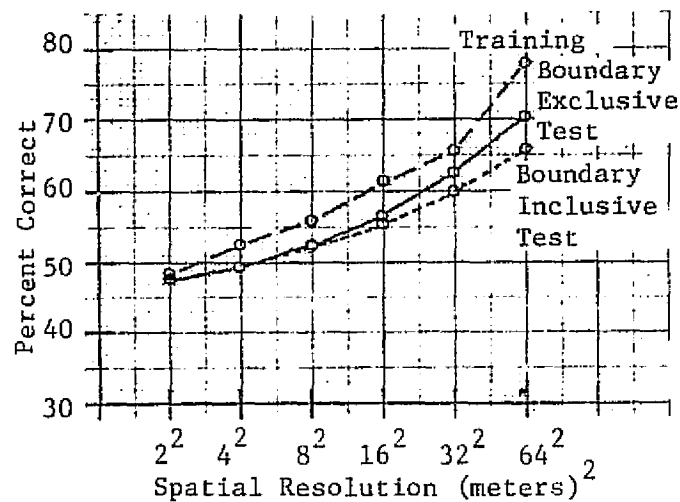(b) Changes For Training Sets
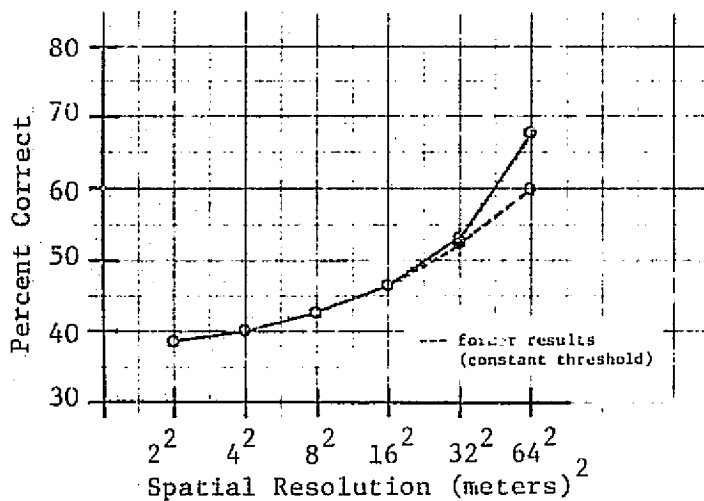
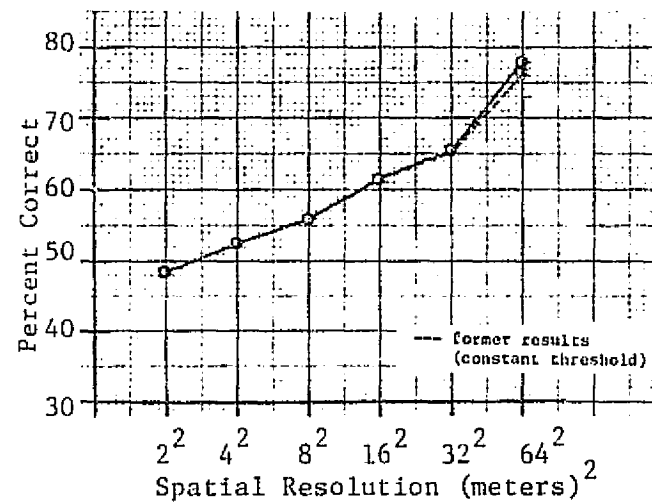(c) Changes For Boundary Exclusive Test Sets
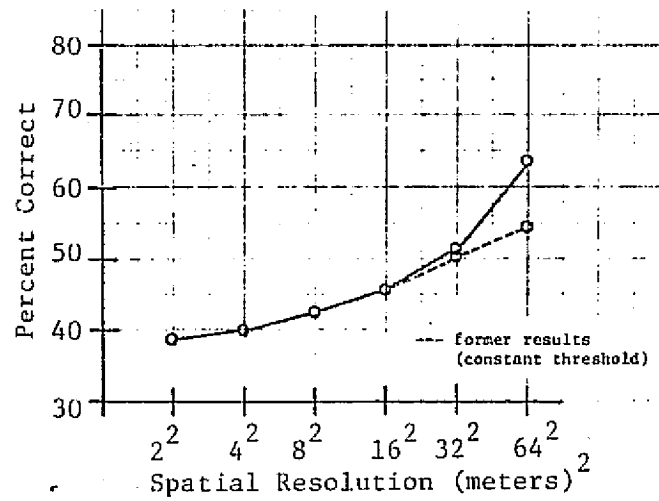
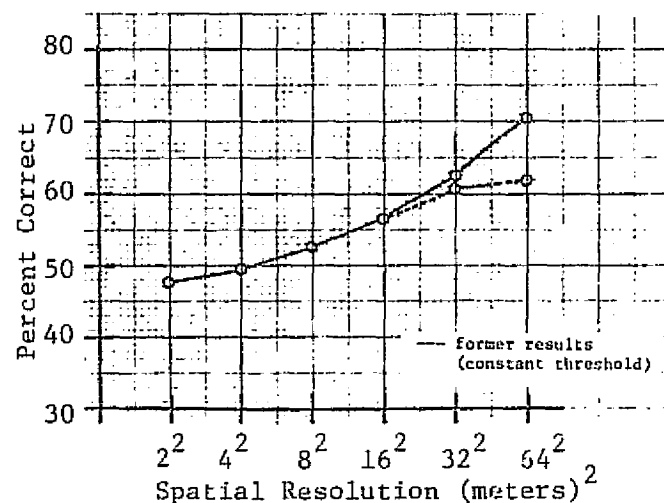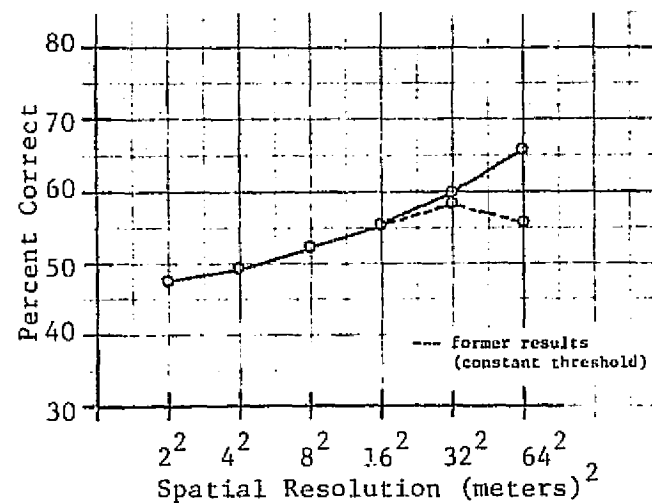(d) Changes For Boundary Inclusive Test Sets

FIGURE 19. EFFECTS OF ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION OF
SPATIAL RESOLUTION FOR CONDITION CLASSES OF DATA SEGMENT 1

(a) Revised Results For All Data Sets
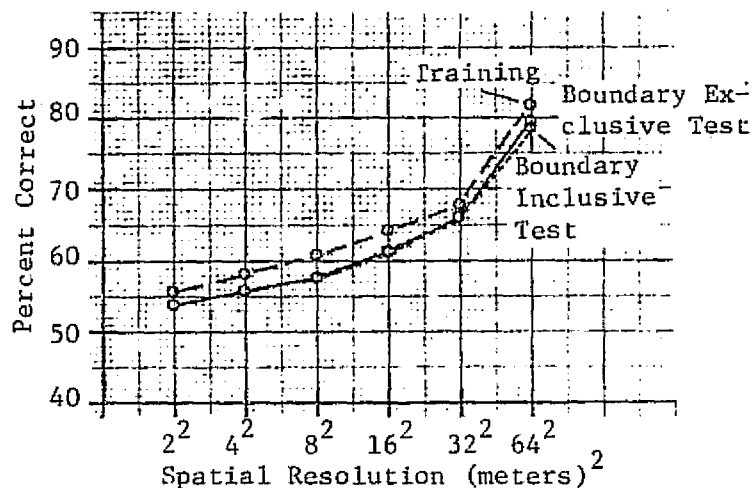
(b) Changes for Training Sets
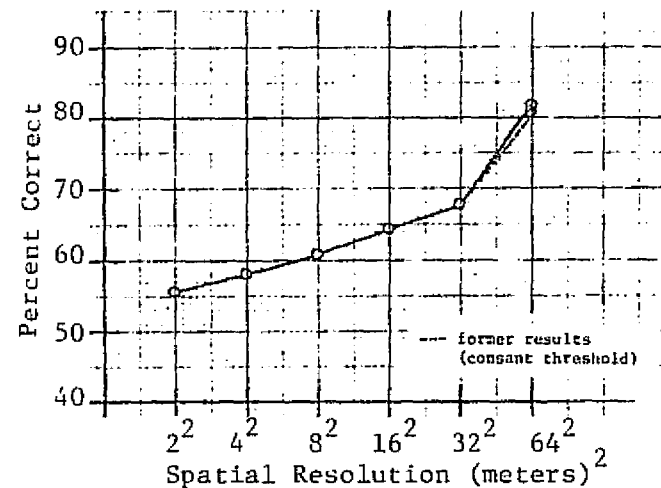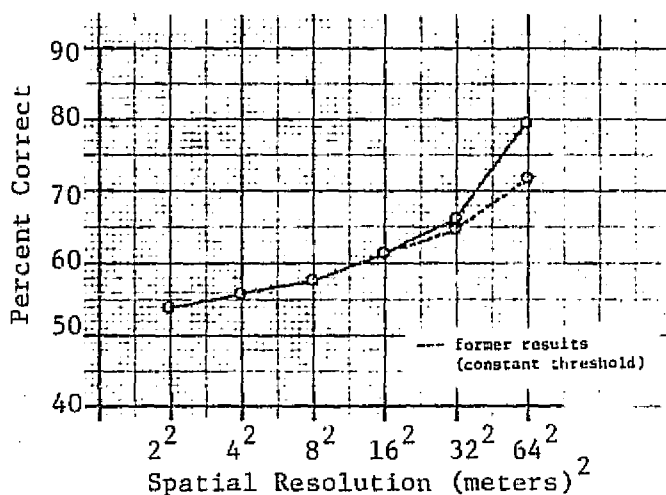
(c) Changes For Boundary Exclusive Test Sets

(d) Changes For Boundary Inclusive Test Sets

FIGURE 20.   EFFECTS OF ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION OF
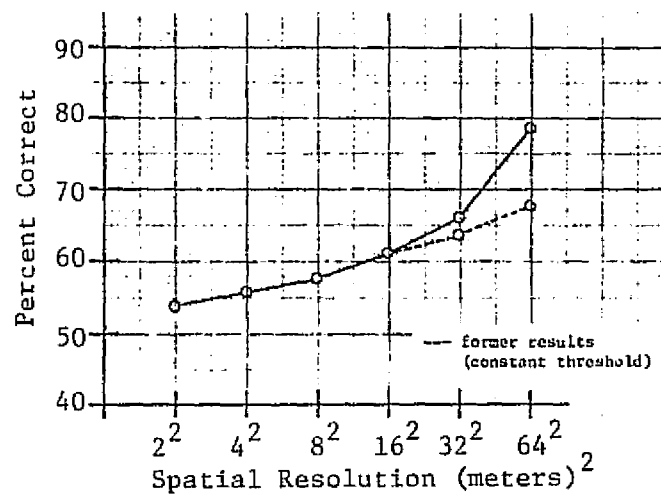SPATIAL RESOLUTION FOR GROWTH STAGES OF DATA SEGMENT 1

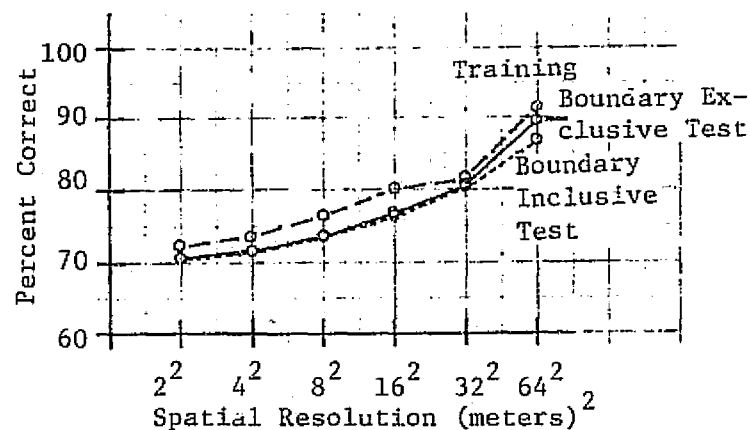(a) Revised For All Data Sets

(b) Changes For Training Sets

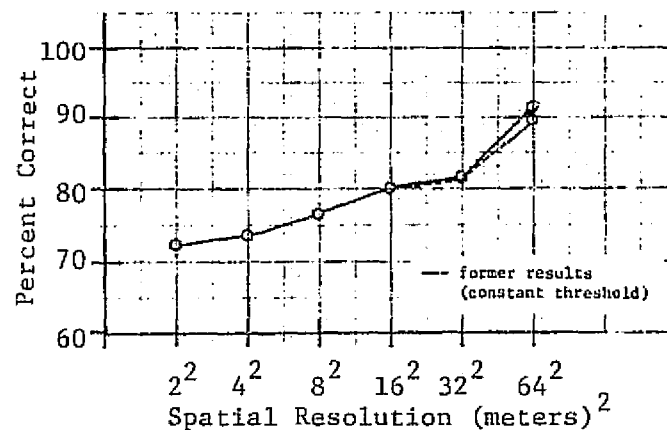(c) Changes For Boundary Exclusive Test Sets

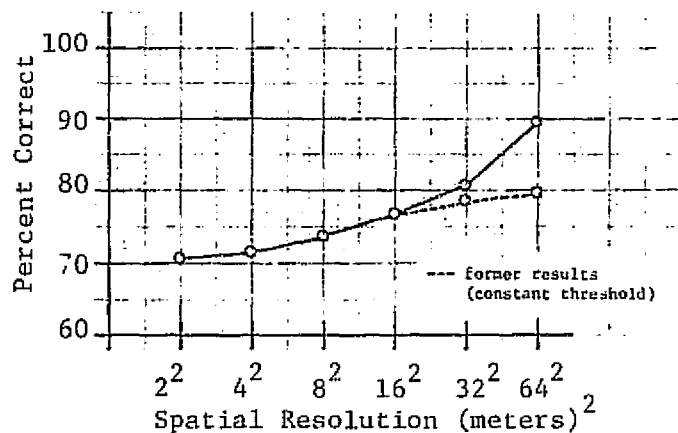(d) Changes For Boundary Inclusive Test Sets

FIGURE 21.   EFFECTS OF ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION OF
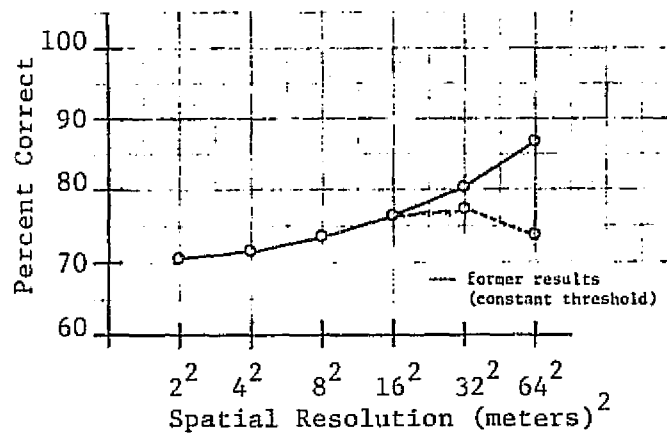SPATIAL RESOLUTION FOR COVER TYPES OF DATA SEGMENT 1

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(a) Revised Results For All Data Sets
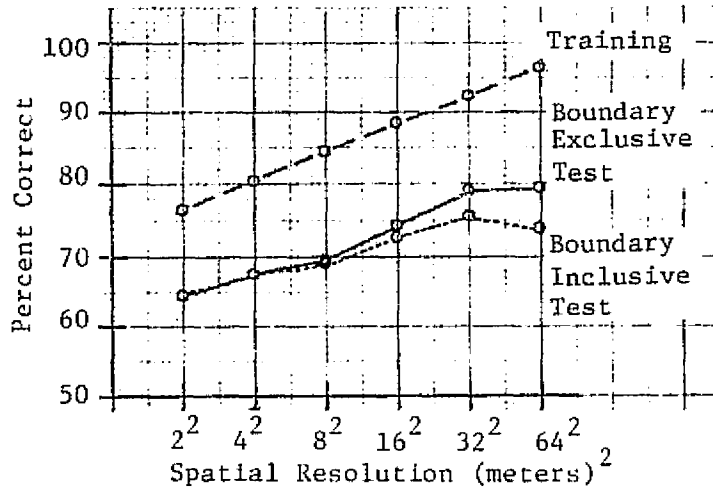
(b) Changes For Training Sets

(c) Changes For Boundary Exclusive Test Sets

(d) Changes For Boundary Inclusive Test Sets

FIGURE 22, EFFECTS OF ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION OF SPATIAL RESOLUTION FOR PHYSIOGNOMY IN DATA SEGMENT 1.

(a) Revised Results For All Data Sets

(b) Changes for Training Sets
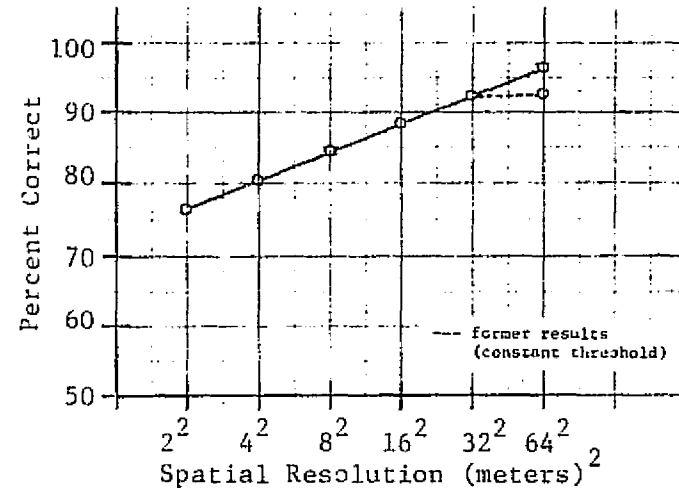
(c) Changes For Boundary Exclusive Test Set

(d) Changes For Boundary Inclusive Test Set

FIGURE 23. EFFECTS OF ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION OF SPATIAL RESOLUTION FOR CONDITION CLASSES OF DATA SEGMENT 2

(a) Revised Results For All Data Sets

(b) Changes For Training Sets

(c) Changes For Boundary Exclusive Test Set
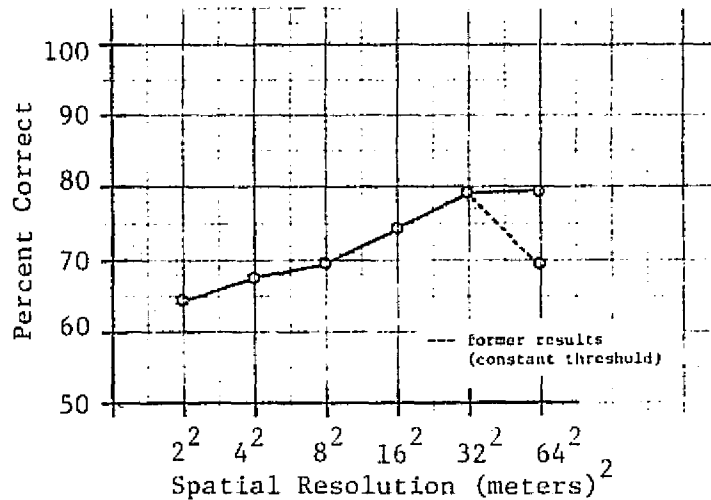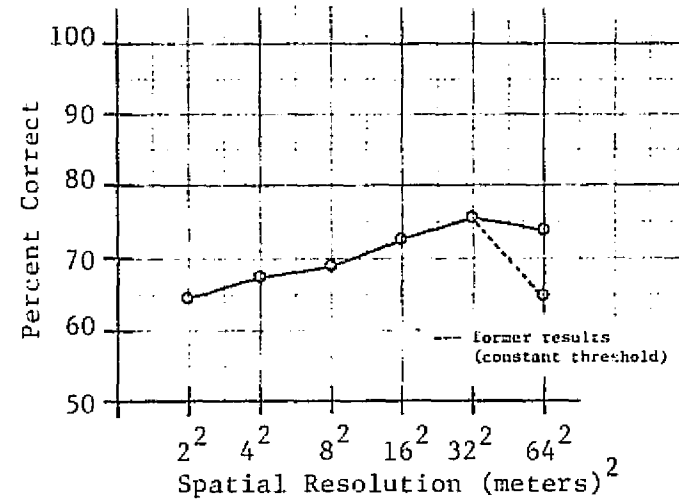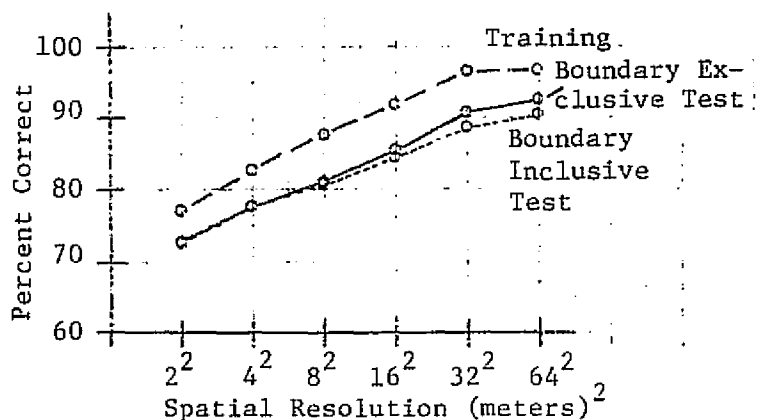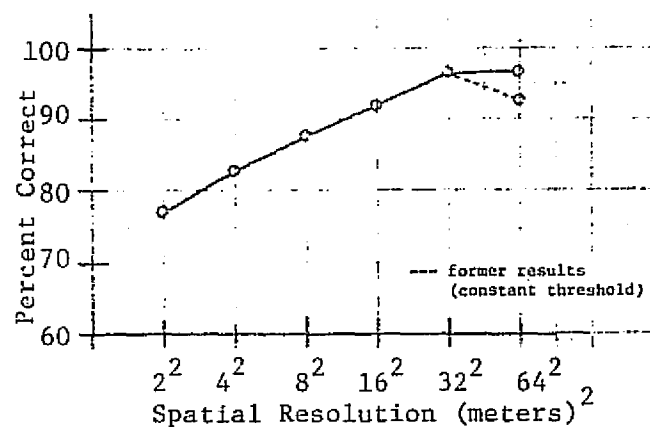
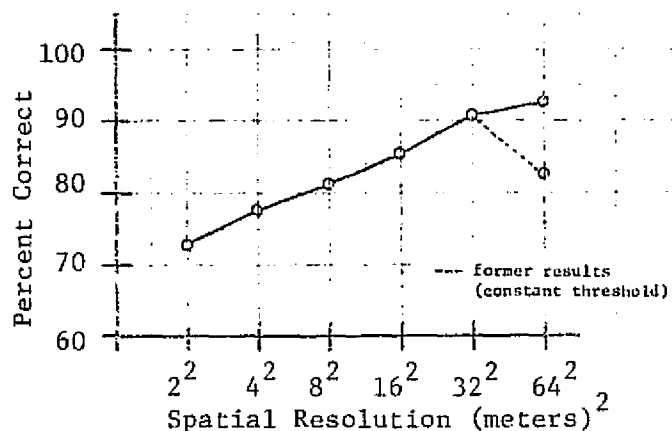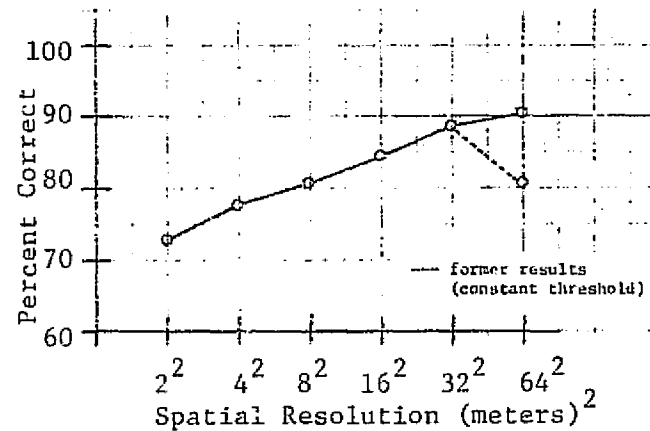(d) Changes For Boundary Inclusive Test Sets

FIGURE 24.   EFFECTS OF THE ADJUSTED DECISION THRESHOLDS ON CLASSIFICATION ACCURACY AS A FUNCTION
OF SPATIAL RESOLUTION FOR PHYSIOGNOMY IN DATA SEGMENT 2

Figures 19-22 present similar plots for each of the four hierarchies of Data Segment 1. In every case for threshold adjusted results (Plot (a) of Figures 19 through 22), the highest accuracies are for the $(64 \text{ meters})^2$ case. For training and test sets, there is a gradual increase in performance as spatial resolution coarsens with a larger increase at $(64 \text{ meters})^2$. The plots which compare the threshold adjusted results with the constant threshold results (Part (b)-(d) of Figures 19-22) show a significant improvement only for $(64 \text{ meters})^2$ test sets. These increases in classification accuracy change the trend of boundary inclusive test sets for growth stages and physiognomy (Figures 20(d) and 22(d)) which previously indicated that the $(32 \text{ meters})^2$ resolution gave the highest accuracy.

Figures 23 and 24 are plots of the results for the two hierarchies of Data Segment 2. Plot (a) of each figure indicates that in most cases, the $(64 \text{ meters})^2$ resolution is slightly better than the $(32 \text{ meters})^2$, but the amount of improvement in classification accuracy decreases after $(32 \text{ meters})^2$ for all cases except training sets of the condition class hierarchy. In contrast, the previous results (Plots (b)-(d) of Figures 23 and 24) indicated a very significant drop in accuracy for the $(64 \text{ meters})^2$ case as compared to $(32 \text{ meters})^2$ for test sets.

One explanation of the slight increase in accuracy for the $(64 \text{ meters})^2$ case of Data Segment 2 is that, for physiognomic training sets (Figure 24(a), $(32 \text{ meters})^2$ accuracy approaches 100 percent. For all resolutions, the overall accuracies of both training and test sets are always higher in Data Segment 2 than in Data Segment 1. These higher accuracies reflect the fact that a classification of Data Segment 2 is trying to separate forest features which are more readily distinguishable than those in Data Segment 1 and represents a different problem. The small difference in accuracy seen for the $(64 \text{ meters})^2$ case compared to the $(32 \text{ meters})^2$ case in Data Segment 2, thus, may represent a plateau for classification of that

data which is apparent for the training set case for physiognomy
(Figure 24(a)). Data Segment 1 apparently has not reached the limiting
spatial resolution for classification accuracy of that data set.

3.3.2 INFLUENCE ON AREA PROPORTION ESTIMATION

The proportion of unclassified elements greatly affected the esti-
mation of the proportion of each forest feature present in the area.
Since the unclassified elements could not be included in the proportions
of any of the forest features, estimates were lowered producing situa-
tions in which every forest feature was underestimated.

In Figures 25 and 26, RMS error is plotted as a function of spatial
resolution for the physiognomy hierarchies of both data segments.

RMS errors for each data segment were calculated as

$$E_{RMS} = \left(\frac{1}{N} \sum_{i=1}^{N} (p_i - \hat{p}_i)^2 \right)^{\frac{1}{2}}.$$

where: p_i = ground truth proportion for one feature in the
test area,

$\hat{p}_i$ = estimated proportion for the same feature in the
test area,

N = number of features considered.

Figure 25 gives RMS error calculated from proportions of all elements in
the test area while Figure 26 gives RMS error calculated from proportions
using only classified elements. There is not a significant change in
the results displayed in Figure 26 for threshold adjusted versus threshold
constant results. However, Figure 25 shows a marked decrease in the
threshold-adjusted RMS error at $(64 \text{ meters})^2$ for both data segments.
Thus, when a large percentage of the elements in an area were unclassified
and these elements were included in proportion calculations, the RMS
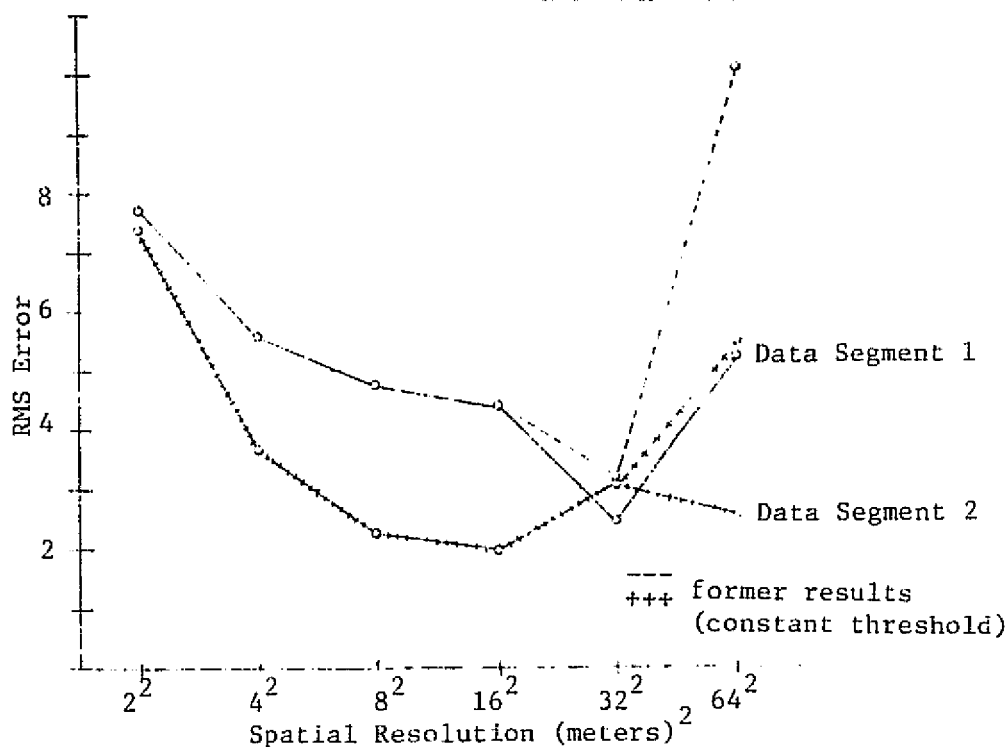error was significantly higher.

FIGURE 25. RMS ERROR, CALCULATED FOR ALL ELEMENTS IN EACH DATA SEGMENT, PLOTTED AS A FUNCTION OF RESOLUTION
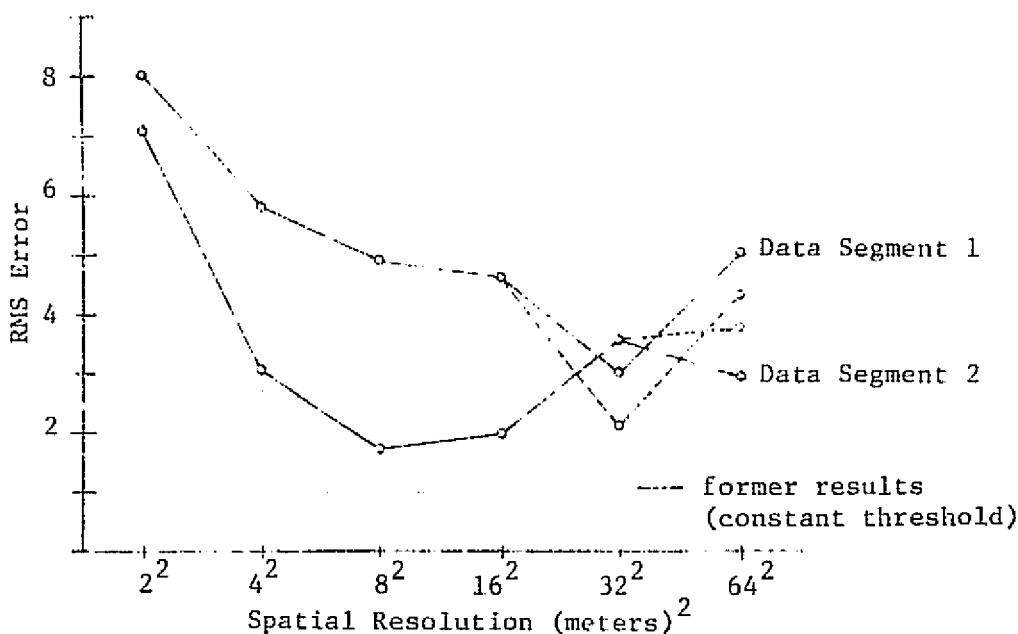

FIGURE 26. RMS ERROR, CALCULATED FOR ONLY CLASSIFIED ELEMENTS IN EACH DATA SEGMENT, PLOTTED AS A FUNCTION OF SPATIAL RESOLUTION

Figures 27-30 are plots of the difference in percentage points
of the forest feature proportions as determined by ground truth and
estimated proportions of features. In Figures 27 and 28, the estimated
proportions were calculated from all elements in the test area, but
Figures 29 and 30 give results using only classified elements. The
major difference in using the threshold adjusted results instead of the
constant threshold results is that even at coarse spatial resolutions
the results for all elements is very similar to the results for only
classified elements. The threshold adjusted proportions seem to be
a much more valid assessment of the accuracy attainable with proportion
estimation since we no longer have the situation where everything is
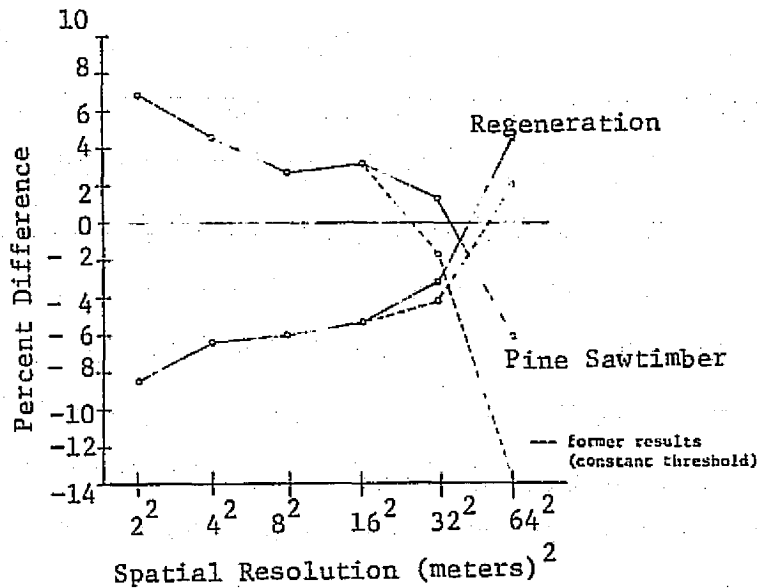underestimated as for the constant threshold results in Figure 28.

FIGURE 27. PERCENT DIFFERENCE BETWEEN TRUE GROUND PROPORTIONS AND ESTIMATED PROPORTIONS CALCULATED FOR ALL ELEMENTS OF DATA SEGMENT 1

FIGURE 28. PERCENT DIFFERENCE BETWEEN TRUE GROUND PROPORTIONS AND ESTIMATED PROPORTIONS CALCULATED FOR ALL ELEMENTS OF DATA SEGMENT 2
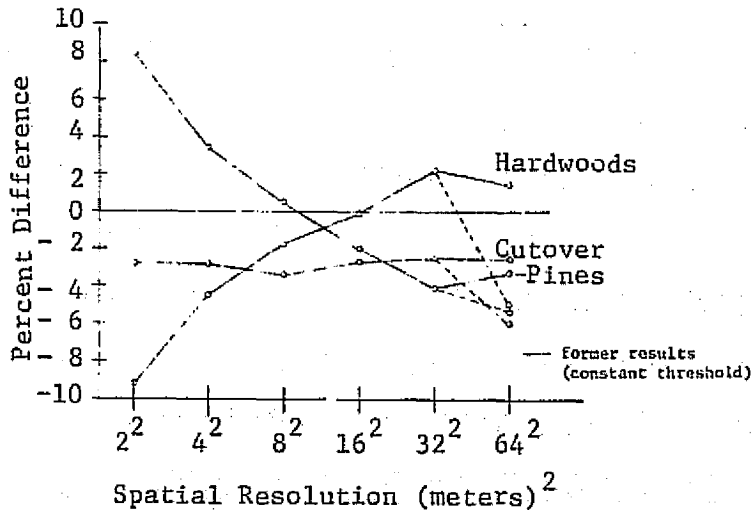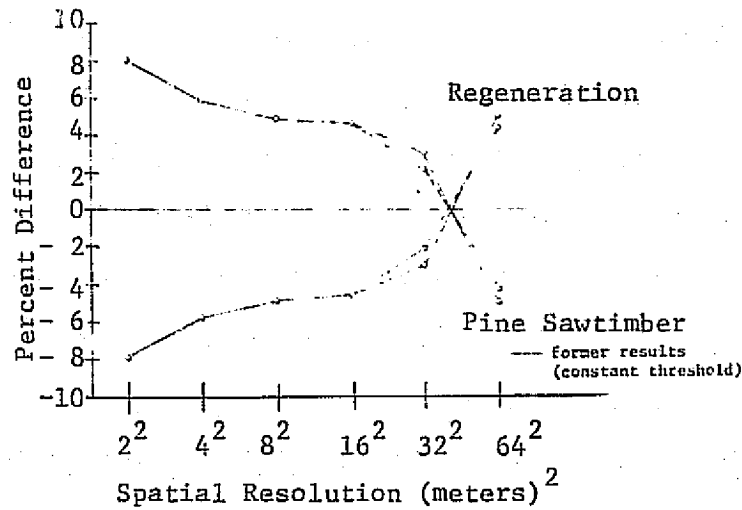
FIGURE 29. PERCENT DIFFERENCE BETWEEN TRUE GROUND PROPORTIONS AND ESTIMA-
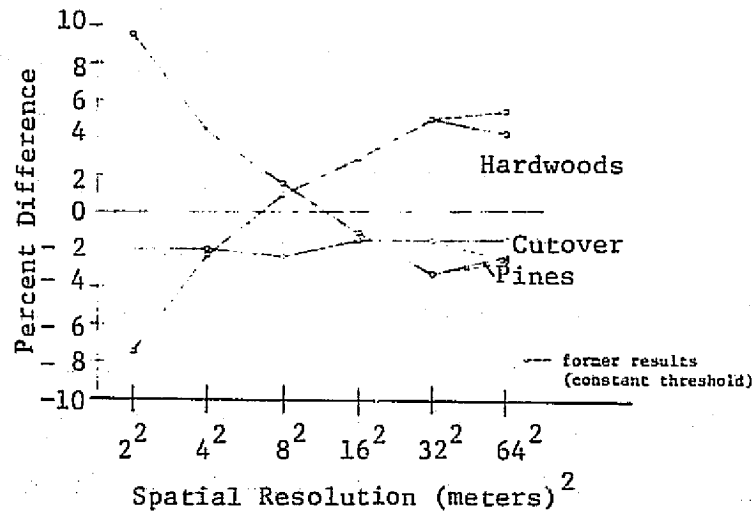TED PROPORTIONS CALCULATED FOR CLASSIFIED ELEMENTS OF DATA SEGMENT 1

FIGURE 30. PERCENT DIFFERENCE BETWEEN TRUE GROUND PROPORTIONS AND ESTIMA-
TED PROPORTIONS CALCULATED FOR CLASSIFIED ELEMENTS OF DATA SEGMENT 2

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CONCLUSIONS

In order to explain large variations in classification accuracy
that were manifested by individual condition class forest features in
processed multispectral scanner data and the inconsistent changes in
accuracy among the features that were noted as spatial resolution was
degraded, we generated two-channel ellipse plots which illustrated the
forest feature signatures at several cases of resolution. Analysis of
the plots show that the capability of signatures to identify their
respective features is dependent on the relationship of each signature
to all others in the signature set. Signatures for which considerable
statistical overlap or competition exists with neighboring signatures
will produce low classification performance for their respective features
due to large amounts of resolution element misclassification. In such
situations, signatures with small variance and high correlation (tighter
distributions) may have an advantage over signatures with large variance
and/or lower correlation. The use of multiple signatures to characterize
obviously nonuniform areas within a feature is one method for producing
signatures of smaller variance that would improve feature classification
performance.

Reductions in signature variance that occur in data of degraded
spatial resolution cannot be said to improve classification performance
for all forest features a priori. Signatures for forest features having
large variances and small mean separations may continue to have much
overlapping variance in coarser resolution data, thus causing little
or no change in the total proportion of resolution elements misclassified
within their feature areas.

A simulation of feature classification was performed under
the assumption that the data values within feature training areas
at each case of spatial resolution had multivariate normal distributions.
A comparison of the "expected" performance to the real data classification

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performance suggests that the real data values within training areas
tended to approach a normal distribution more closely as spatial resolution
was degraded. This trend is attributed to the averaging of spectral
irregularities within resolution elements of progressively larger size
and the consequent decreasing likelihood of different modes that might
occur within distributions of fine resolution data.

Small differences in rates of decrease for determinant values
were seen to exist among the signatures of Data Segment 1 as spatial
resolution was degraded. It is suggested that such non-uniform rates
of change may be indicative of some textural attribute that varies
with spatial resolution. In addition, evidence was provided to
suggest that correlations between the channels of a spectral signature
decrease as spatial resolution is degraded.

In the second part of the study, adjustments of the threshold
to maintain a constant proportion of unclassified elements among all
cases of spatial resolution significantly increases the overall classifi-
cation accuracy for $(64 \text{ meters})^2$ data for both data segments. As a re-
sult of the increased accuracies for $(64 \text{ meters})^2$ data, the resolution
which provides the most accurate over all element-by-element classifica-
tion results is $(64 \text{ meters})^2$ for threshold-adjusted results. The in-
crease from $(32 \text{ meters})^2$ to $(64 \text{ meters})^2$ is much more dramatic for
Data Segment 1 than Data Segment 2. Accuracies are higher for Data
Segment 2 than Data Segment 1 for all resolutions, thus the fact that
the increases are relatively slight from $(32)^2$ to $(64 \text{ meters})^2$ may be
due to the already high $(32 \text{ meters})^2$ accuracy. Classification results
using adjusted thresholds, thus, indicate that the optimum spatial
resolution for classification accuracy was $(64 \text{ meters})^2$ not $(32 \text{ meters})^2$.

As a result of this study, we recommend for future operational
systems that decision thresholds not be set arbitrarily to a constant
value. For example in this study, where all ground features were repre-
sented by training data, the area proportion estimations should have been
determined using non-thresholded classifications which would have forced
the classification of all elements.

REFERENCES

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